Information Disclosure via Platform Endorsement in Online Healthcare

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Abstract

Online healthcare platforms enhance healthcare access and equity by removing geographic barriers and facilitating doctors to serve underprivileged patients. However, they exacerbate information asymmetry due to the vast number of doctors available online. To mitigate this and to motivate leading doctors to improve their practices, platforms have introduced endorsements, awarding select doctors badges for exceptional performance. This study investigates the impact of platform endorsement on both patients' demand and doctors' decisions on pricing, quantity, the mix between free and paid services, and quality by exploiting a leading Chinese platform's "Good Doctor of the Year" endorsement program. Using the Generalized Synthetic Control method, we find that endorsement boosts demand for endorsed doctors, who respond by increasing prices and provision of paid services while maintaining service quality. However, we find that endorsement leads to an unintended consequence of a decrease in free services provided by endorsed doctors, thereby disadvantaging underprivileged patients. Notably, this reduction in free services is more pronounced among "pro-social" doctors due to their reluctance to raise prices and limited capacity. These findings highlight the need for platforms and policymakers to understand the nuanced impacts of information disclosure on doctors' decisions and the potential unequal effects across different groups of patients in online healthcare, a sector with significant societal implications.

Keywords: online healthcare, platform endorsement, doctor consultations, paid services, free services

1 Introduction

Online healthcare has become increasingly popular among patients and doctors, especially after the COVID-19 pandemic. In 2022, online healthcare markets surpassed $71.5 billion and are expected to grow by 12.5% annually from 2023 to 2032.[1] In this evolving healthcare landscape, online platforms are emerging as a critical component in enhancing healthcare access and equity (WHO, 2010). By removing geographical barriers and enabling efficient time use, these platforms empower doctors to extend their expertise to a broader range of patients through both *paid* and *free* consultations. The latter, targeted at underprivileged patients, is a widespread practice in both developing and developed countries.[2] Consequently, online healthcare platforms have the potential to significantly enhance doctors' service provision and concurrently reduce healthcare disparities.

Despite this potential, the huge number of doctors available on the platforms makes it difficult for patients to assess the true quality of doctors, exacerbating the profound information asymmetry problem in healthcare (Arrow, 1963). To mitigate this problem, platforms have introduced "platform endorsement," using data to select and award leading doctors with badges like "Doctor of the Year" on Doctify.com (UK) and on Haodf.com (China). This approach is designed to assist patients in making informed choices by facilitating the identification of leading doctors while also encouraging these doctors to enhance their engagement in providing both paid and free services and to uphold their service quality. However, the effectiveness of information disclosure via platform endorsement in achieving these intended

[1]Global Market Insights, 2023

[2]Doctors providing free services is a common practice observed around the world. For example, over 1,200 Free and Charitable Clinics within the US National Association of Free & Charitable Clinics rely on volunteer doctor workforces to deliver cost-free services; see https://nafcclinics.org/. Organizations like Doctors of the World have spearheaded 350 programs across 80 countries, led by over 3,000 volunteers, to ensure healthcare access for marginalized populations; see https://www.doctorsoftheworld.org.uk/who-we-are/. Additionally, between 2013 and 2017, approximately 60 million free medical consultations were provided in impoverished areas through China's "Service for People's Health Initiative," led by the National Health and Family Planning Commission; see https://www.gov.cn/xinwen/2017-09/10/content_5224139.htm. Online platforms have made the delivery of such free services more feasible, as demonstrated by the daily provision of over 120,000 free online consultations to underprivileged patients during the peak of the COVID-19 pandemic. https://cn.chinadaily.com.cn/a/202003/12/WS5e69b109a3107bb6b57a5fbe.html. All sources are retrieved on November 6, 2023.

outcomes remains uncertain.

In this study, we examine the impact of information disclosure via platform endorsement in online healthcare for both doctors and patients. Specifically, we quantify the impact of platform endorsement on a range of outcomes, including service price, service quantity, the mix between free and paid services, and service quality. While previous research has explored similar endorsement tools in e-commerce and content-sharing platforms (detailed in the literature section), online healthcare presents three important differences. First, healthcare decisions are inherently more complex, involving not only considerations of price and quantity but also quality and service type. All these factors are critical in discussions of healthcare access and equity. Second, these platforms allow doctors to offer a mix of free and paid services, a combination not yet examined in prior research. This combination, coupled with the time constraints faced by doctors, creates theoretical ambiguity in the impact of platform endorsement on doctors' time allocation between these service types, leading to varied effects across different patient groups and on the platform's long-term growth. Third, given the significant societal impact of healthcare, there is a compelling need for a focused exploration of platform endorsement in this sector.

To study the impact of platform endorsement in online healthcare, we focus on *haodf.com*, a leading online doctor consultation platform in China. This platform introduced the "Good Doctor of the Year" endorsement program in 2013 and has since been annually endorsing a select set of doctors. Combining proprietary data shared by the platform and supplemental data scraped by a third party, we analyze a weekly panel of 2,229 doctors in a two-year period between 2018 and 2019. The focal treatment is "Good Doctor of 2018" endorsement, released in the second week of 2019. Out of the 2,229 doctors, 156 who were endorsed for the first time in 2019 form the treatment group while the remaining 2,073 doctors who have never received the endorsement serve as the control group. The dataset covers 53 weeks in the pretreatment period and 51 weeks in the posttreatment period.

To estimate the effects of platform endorsement on patients and doctors, a natural approach is to use a difference-in-differences (DiD) specification that compares changes before and after the endorsement of endorsed doctors relative to the control group of unendorsed doctors. However, one concern is the possibility of time-varying unobserved factors that differ between endorsed and unendorsed doctors. To account for potential unobserved factors, we employ the generalized synthetic control (GSC) framework, which constructs a synthetic control group for endorsed doctors. We then compare pretreatment and posttreatment changes for endorsed doctors against this constructed synthetic control group to estimate the effects of endorsement. We further show the robustness of our results with alternative approaches, including standard difference-in-differences (DiD) and the propsensity score matching with difference-in-differences (PSM-DiD).

We first present the average treatment effects of platform endorsement among endorsed doctors. For paid services, platform endorsement leads endorsed doctors to raise their prices by 8.7%. Despite this price increase, there is a significant rise in patient requests, resulting in a 19.7% increase in the quantity of paid services delivered. This result is intuitive because endorsement serves as a positive quality signal that could drive up demand and price premiums. However, contrary to some previous research where researchers find that status signaling, similar to endorsement, could incentivize health workers to conduct more volunteer work (Fracchia et al., 2023), we observe a substantial reduction of 35.2% in the provision of free services by endorsed doctors postendorsement. Lastly, we find that doctors are able to maintain their service quality following endorsement, evidenced by more communication with patients within a consultation and no significant changes in patient reviews, repeat consultation rates, or waiting time.

Based on the estimated effects on free and paid service provision, we quantify that platform endorsement leads to a 5.2% increase in the total service provision from endorsed doctors. Specifically, the increase in paid services secures an endorsed doctor an additional average annual revenue of $6,971, an amount approximately equivalent to half the average annual salary of a doctor in China. Collectively, this aggregates to a noteworthy $1.1 million annual surge in revenue channeled through the platform by newly endorsed doctors. However, this financial benefit is offset by a notable decrease in the provision of free services. Our estimates suggest that the shift from free to paid services among newly endorsed doctors has inadvertently led to an annual reduction of 27,000 free consultations for underprivileged patients. This reduction could hinder the platform's long-term growth, considering that free services might have positive spillover effects on paid services (Deng et al., 2023; Liu et al., 2014) and that this reduction of free services could adversely affect the platform's corporate social responsibility image and brand equity.[3]

Since the reduction of free services is concerning for both the platform and society, we next explore the heterogeneous reactions across doctors towards endorsement to better understand this reduction. Doctors are categorized into two groups: "pro-social doctors" and "non-pro-social doctors," defined based on their provision of free services relative to the median during the pretreatment period.[4] By comparing the two groups, we find that the reduction of free services after endorsement is mainly driven by pro-social doctors. The reasoning behind this is that these pro-social doctors, after endorsement, tend to avoid significant price increases, leading to increased patient demand and thus higher provision of their paid services. Due to capacity constraints, they have to substantially reduce their free service provision as a result. In contrast, non-pro-social doctors, responding to the endorsement, tend to significantly raise their prices, which curtails the growth in patients' demand for their paid services and thus minimally impacts their provision of free services.

Our study makes three key contributions. First, despite extensive research on the impact

[3]Volunteer work in the healthcare sector for underprivileged populations serves as a significant social good (Michelson, 2019), enhancing the platform's corporate social responsibility (CSR) image (Plewa et al., 2015). A positive CSR image is instrumental in establishing a company's brand and ensuring its sustained growth (Wang et al., 2015). Noronha et al. (2013) document a significant increase in CSR legislation and guidelines for Chinese companies since 2001, underscoring the necessity for firms in China to engage in social responsibility.

[4]Note that the pretreatment free service provision, or pro-social activities, could be driven by either pure altruistic motives (Galizzi et al., 2023)—where doctors genuinely care about the welfare of underprivileged patients—or impure altruistic motives—where doctors provide free services in hopes of gaining reputation (Berman and Silver, 2022). Regardless of the underlying motives, the platform's objective is to ensure that endorsement does not deter these pro-social activities.

of information disclosure on doctors' *offline* healthcare decision-making, we provide the first study to quantify the impact of information disclosure on doctors' *online* healthcare decision-making. Second, our study documents an unintended consequence of information disclosure via platform endorsement: a reduction in the provision of free services by leading doctors for underprivileged patients, thereby exacerbating issues of healthcare equality and access. This finding highlights the nuanced social implications of information disclosure in healthcare, influenced by doctors' multi-dimensional decisions. Third, our study is the first to examine the impact of information disclosure via platform endorsement in a digital platform offering *both free and paid services*. This is increasingly relevant as more platforms, such as legal consultation platforms (*Avvo* and *LawGuru*), online education platforms (*Udemy* and *Teachable*), and content-sharing platforms (*Substack* and *Patreon*), adopt mixed free-paid models. Our findings highlight the necessity for these platforms to consider how information disclosure tools such as endorsements affect the relative allocation between free and paid services and their varied impacts on different user groups and platforms' long-term growth. Overall, our contributions are likely to be beneficial to platforms, social planners and healthcare providers.

2 Related Literature

This paper contributes to three streams of literature.

First, this paper relates closely to the extensive literature regarding information disclosure in the healthcare industry. Depending on the source of the information, one substream of research has investigated the impact of the information sourced from healthcare providers on patients' decisions or outcomes, covering clinical attributes like mortality and readmission rates (Cutler et al., 2004; Avdic et al., 2019), patient health outcomes (Gutacker et al., 2016) and satisfaction (Avdic et al., 2019), physician payments (Guo et al., 2020), and composite quality index (Santos et al., 2017). Another substream of research has explored the impact of information sourced from patients such as patient ratings and reviews on the choice of healthcare providers (Luca and Vats, 2013; Lu and Rui, 2018; Bensnes and Huitfeldt, 2021; Xu et al., 2021; Chen and Lee, 2024; Brown et al., 2023). Our study adds to this literature in two ways. First, while prior research predominantly focused on how information influences offline healthcare choices, we are the first, to our knowledge, to examine its impact on patients' online healthcare choices and doctors' online consultation behaviors. Second, we explore a new approach to information disclosure in healthcare: platform endorsement. This novelty involves platforms using comprehensive data to endorse select doctors with badges, providing an independent perspective and a straightforward binary measure, which sets it apart from traditional information sourced from healthcare providers or patients.

Second, our paper adds to the empirical literature on unintended consequences due to information disclosure in the healthcare domain, which arises from the complex responses of healthcare providers. Dranove et al. (2003) and Werner and Asch (2005) highlight that disclosing patient outcomes through healthcare report cards, while addressing information asymmetry, may lead doctors and hospitals to avoid treating complex and severely ill patients, ultimately diminishing patient well-being, especially for vulnerable individuals. Similarly, Yoon (2020) finds that cardiac surgery report cards can adversely affect high-risk patients due to congestion of the best healthcare providers. Additionally, Lu (2012) investigates the Nursing Home Quality Initiative in the U.S. and shows that information disclosure can cause nursing homes to allocate less effort to unreported quality dimensions, thereby deteriorating unreported areas. Our study indicates that platform endorsement leads endorsed doctors to increase their provision of paid services at the cost of reducing free services, adversely affecting underprivileged patients. We further document that this reduction in free services is more pronounced among pro-social doctors due to their constrained capacity and hesitance to raise prices for paid services.

Third, this study contributes to the literature on the market outcomes of platform endorsement, or similar tools such as platform certification and awards. Previous research has predominantly focused on two scenarios: free-only service settings and paid-only service settings. In free-only settings, tools similar to platform endorsement have been shown to incentivize voluntary editors to stay on Wikipedia (Gallus, 2017), boost engagement on user-generated content platforms like Reddit (Burtch et al., 2022), and increase content creation on image-sharing platforms (Huang and Narayanan, 2020; Huang et al., 2022). Conversely, in paid-only settings, endorsement-like tools have been shown to consistently increase paid service offerings in various domains like eBay (Elfenbein et al., 2015; Hui et al., 2016), Airbnb (Dewan et al., 2023), and online freelancing (Bairathi et al., 2022). Our study contributes to this literature by investigating a setting where both free and paid services coexist. As more platforms across various domains, including legal services, online learning, and content-sharing, adopt this mixed free-paid environment, our study underscores the importance of considering the substitution between these two service types as a result of platform endorsement and its heterogeneous consequences for various user groups. Furthermore, while previous research has extensively explored the impact of platform endorsement from the demand side, its effects on the supply side remain underexplored. Our study advances our understanding by highlighting the significance of the supply side, including decisions on price, quantity, quality, and the mix of free and paid services. Each of these aspects holds particular significance in the healthcare sector.

3 Institutional Setting

The online healthcare sector in China has experienced rapid growth in the past decade. Between 2013 and 2019, investments in China's online healthcare sector surged from $675 million to $5.7 billion.[5] Within this sector, online doctor consultations constitute the largest component and were primarily provided by third-party platforms before the onset of the Covid-19 pandemic (Cheng et al., 2022).[6] These platforms serve patients across the country,

[5] Fastdata, 2021. Report on Internet Health Industry in China 2020.

[6] Since 2020, some hospitals have started to offer online doctor consultations directly. Source: https://www.gov.cn/xinwen/2021-03/26/content_5595808.htm, retrieved on November 6, 2023.

providing them with the convenience of consulting doctors remotely. In 2020, the number of active users seeking online doctor consultations reached 400 million.[7] This sector is projected to maintain an annual growth rate of 11.5% in the coming years, underscoring its significance to both consumers and the economy.[8]

We focus on one of the leading third-party online doctor consultation platforms in China — *Haodf* (www.haodf.com), which translates to "Good Doctor" in English. Established in 2006, the platform has attracted nearly 210,000 licensed doctors to register by 2019, accounting for 10.4% of all licensed doctors employed by hospitals in the country.[9] *Haodf* stands out among other online doctor consultation platforms in China due to the exceptional quality of its registered doctors. Approximately 78% of these doctors are affiliated with top-tier public hospitals in the country. These doctors are highly skilled, experienced, and often leading figures in their respective fields by contributing to medical research and staying at the forefront of the healthcare industry. The platform offers a wide range of medical specialties, spanning 28 departments (see Web Appendix Figure A1 for the list of departments and service volume distribution across departments). The limited accessibility and lengthy waiting time in public hospitals have driven patients towards online doctor consultations. By 2019, the platform had served nearly 63 million patients, facilitating approximately 7.1 million doctor consultations within that year alone.[10] Notably, in 2020, the platform provided a daily average of 10,000 free online consultations to underprivileged patients.[11]

[7] Fastdata, 2021. Report on Internet Health Industry in China 2020.

[8] Source: https://data.worldbank.org/indicator/SH.XPD.OOPC.PP.CD?locations=CN, retrieved on November 6, 2023.

[9] The number of registered doctors on the platform is reported at https://www.vbdata.cn/45870, retrieved on November 6, 2023. The total number of doctors working in hospitals in China was 2,028,296 in 2019, according to 2020 China Health Statistical Yearbook, page 26.

[10] Source: https://www.sohu.com/a/394919067_115980, retrieved on November 6, 2023.

[11] https://cn.chinadaily.com.cn/a/202003/12/WS5e69b109a3107bb6b57a5fbe.html, retrieved on November 6, 2023.

3.1 Doctors on the Platform

To register on the platform, doctors must possess two qualifications necessary for legal medical practice in China: the Medical Practitioner's License and the Doctor's Qualification Certificate. Additionally, they must maintain a full-time affiliation with a hospital.[12] Upon registration, doctors have the flexibility to select from two primary types of services: paid and free services. These options offer distinct benefits to doctors. Paid services primarily offer financial rewards to doctors, while free services, although lacking monetary compensation, hold intrinsic value for doctors who place importance on providing healthcare services to the underprivileged.

Paid services on the platform are offered in two formats: text/image and phone call consultations. Text/image consultations allow for the exchange of medical information, such as scan results and test reports, through images and text messages available through both the platform's web and App portals. Text/image consultations are further categorized into two packages: package 1 allows a 48-hour exchange period with unlimited messaging and package 2 limits the number of messages patients can send. Phone call consultations facilitate live discussions between patients and doctors, typically lasting around eight minutes through the platform's App portal. In both cases, doctors set their service prices, with the platform deducting a fixed percentage of the revenue from each paid service.[13] Free services are provided via the text/image format with a limit on the number of messages patients can send.[14]

[12]Web Appendix Figure A2 displays the histogram depicting the distribution of hours during which doctors engage in phone call consultations. The figure indicates that doctors predominantly offer their services through the platform during lunch breaks or after hours.

[13]The platform did not disclose the precise percentage.

[14]The platform also offers booking services for offline appointments with doctors. However, these booked consultations, along with their payments, occur mostly outside the platform's purview and are thus excluded from our analysis.

3.2 Patients on the Platform

Patients use the online doctor consultation platform for a range of reasons, including managing minor health issues promptly, getting a preliminary diagnosis of health problems, and seeking a second opinion about diagnoses given by other doctors they see offline. To register on the platform, patients need to provide their cellphone number for verification purposes.

Upon registration, patients can choose between paid and free services. For paid services, patients have the flexibility to select their preferred doctor through a simple process. They search for and choose their desired doctor and select the appropriate service format. To initiate a request, patients must submit a comprehensive form that includes detailed medical information such as age, gender, medical history, symptoms, and any specific questions they wish the doctor to address. After sending the request, patients await the doctor's acceptance before commencing the consultation. Following the consultation, patients have the option to provide reviews for the consulted doctor. Patients were responsible for all the expenses because health insurance providers did not provide reimbursements for online consultations during our sample period.

The primary difference between free services and paid services lies in a patient's ability to choose doctors and how soon the consultation will take place. For free services, patients cannot choose a doctor. They submit their request with detailed medical information and wait in a public pool with thousands of other patients, hoping for a doctor to show interest in their case and offer free consultations. Since demand far exceeds supply for free services, over one-third of free service requests did not get picked up by any doctor within seven days, while over 95% of paid service requests got accepted by the patient's desired doctor within 12 hours. This uncertainty of whether a doctor will pick up a case, when it will happen, and which doctor the patient will consult with means that free services are predominantly used by economically underprivileged patients.[15]

[15] The platform does not gather information on patients' income levels. To compare patients who seek free services versus those who seek paid services, we use city average income as a coarse proxy for individual income and regress it on free service usage. This analysis reveals a statistically significant estimate of

3.3 "*Good Doctor of the Year*" Endorsement Program

To assist patients in their search for an appropriate doctor, the platform provides ample information on each doctor. The search result page displays key details such as a doctor's name, medical and academic positions, affiliated hospital, department, average rating, specialty, and price. For more comprehensive information, patients can click into a doctor's profile page, which showcases additional details like service type, education level, patients' reviews, and the number of consultations conducted.

Despite providing detailed information, the platform acknowledges that many patients still face challenges in making decisions, especially when many doctors possess similar attributes. To further facilitate the decision-making process for patients and to encourage leading doctors to continuously improve their practices and engage with the platform, the platform introduced the "Good Doctor of the Year" endorsement program in 2013.[16] This program uses extensive data sourced from both patients and doctors to calculate an aggregate metric. The platform then, based on this metric, identifies and awards a select group of doctors at the beginning of a year with a badge that is prominently displayed on the platform. While the specific selection algorithm remains proprietary, factors considered include service volume, waiting time, and patients' reviews from the previous year. The platform allocates a fixed quota of endorsements for each of the 28 departments, ranging from 3 to 20, roughly proportionate to the total number of registered doctors for each department. This endorsement program is highly selective, with less than 0.3% of doctors ever receiving an endorsement badge. The status of receiving an endorsement does not directly enter into the ranking algorithm. However, an endorsement may impact the service volume a doctor provides, which could, in turn, indirectly affect the doctor's ranking. Therefore, in our anal-

-115.35^{***}(std. err. = 27.60), indicating that patients accessing free services are more likely to live in lower-income cities. Furthermore, our conversations with the platform's director and several leading doctors corroborate that underprivileged patients are the predominant users of free services.

[16]Apart from the "Good Doctor of the Year" endorsement, there were no other major changes in the platform operations during the sample period. Furthermore, the "Good Doctor of the Year" program is the only badge that has been introduced by the platform.

ysis, we quantify the overall impact of platform endorsement, implicitly accounting for its indirect effects through ranking.

Once a doctor receives the endorsement, the platform attaches a badge to the doctor's profile picture, which appears on both the search result page and the doctor's profile page. This badge reflects the total number of "Good Doctor of the Year" endorsements a doctor has accumulated and, once awarded, it remains permanently on the doctor's profile. Figure 1a illustrates a scenario where a doctor goes from having no endorsement to receiving the first one and Figure 1b demonstrates a situation where a doctor's number of endorsements increases from one to two. Given that the change from no badge to having one badge is more prominent to both endorsed doctors and patients, we focus on this group of doctors in our main analysis.

(a) Zero to One (b) One to Two

Figure 1: "Good Doctor of the Year" Endorsement Badge

4 Data

To study the impact of platform endorsement, we obtained proprietary data from the platform and supplemented them with additional data scraped by a third party. The combined data cover a wide range of outcomes, including price, service type, service quantity, and service quality. We provide details on each type of data in detail below.

4.1 Proprietary Data

We obtained proprietary data from the platform covering the period from January 1, 2018 to December 31, 2019. The primary focus is the “Good Doctor of 2018,” which was selected based on doctors’ performances in 2018 and was officially announced at the beginning of the second week of 2019. The endorsement targeted the top doctors in each department, with the number of recipients per department ranging from 3 to 20. For our study, the platform provided data on the top 100 doctors in each of the 28 departments, chosen based on the same performance metrics used for endorsement. This sample selection process ensures that every doctor in our sample had a reasonable chance of being endorsed. After excluding doctors with invalid IDs, our sample size was reduced to 2,752. Within this group, 377 doctors were endorsed with the “Good Doctor of 2018” badge at the start of 2019. Of these, 156 were first-time recipients, forming our treatment group. We also identified 2,073 doctors who had not received any endorsement by 2019, forming our control group. As a result, our final sample includes 2,229 doctors, with a 53-week pretreatment period and a 51-week posttreatment period.

The first set of variables in the proprietary data is related to doctor characteristics. In our sample, the doctors’ average age is 45.3 years (standard deviation = 7.0), 71% are male, 67% hold a Ph.D. degree, and 38% are chief doctors.[17] On average, they have been providing services on the platform for six years (std. dev. = 3.2 years).

The second set of variables is related to services, which are recorded at the consultation level. The data allow us to observe whether a consultation request was accepted by the selected doctor. For accepted consultations, detailed data are available, including service type (paid vs. free, text/image vs. phone call, etc.), service price, consultation time, patient demographics (age, gender, city, and disease type), and patients’ reviews (positive/negative rating and review texts). For phone call consultations, we have further information on the

[17]Public hospital doctors in China are ranked with four technical titles: resident doctor (the most junior), attending doctor, associate chief doctor, and chief doctor (the most senior). All the top 100 doctors across the 28 departments are either associate chief doctors or chief doctors.

purchase time and the start/end times of the phone call, through which we can calculate the waiting time (phone call start time - purchase time) and the consultation duration (phone call end time - start time).

4.2 Supplemental Data

In addition to the proprietary data, we also gathered additional data scraped from the *Haodf.com* website by a third party. A distinctive feature of this platform is that it displays all previous messages exchanged (hiding personal and sensitive information) between patients and doctors in the text/image consultations on a doctor's profile page. The platform discloses this information for several purposes, including providing patients with similar symptoms with insights from past advice given by doctors, enabling patients to assess a doctor's consultation style and quality, and serving as a monitoring tool for doctors' interactions.

We collected all messages from text/image consultations involving our doctor sample throughout the sample period. These data enable us to calculate the number of words sent by a doctor during a consultation, a measure for the doctor's engagement.

4.3 Summary Statistics

In our sample, services offered by doctors can be categorized into free and paid services. Free services constitute 18.6% of the total while paid services make up the remaining 81.4%. Within the paid services, there is further subdivision: 63.7% are for text/image package 1 with a 48-hour limit, 13.1% are for text/image package 2 with a limit on the number of messages, and the remaining 23.2% are for phone call consultations.

For the main analysis, we construct a doctor-week panel by combining the proprietary and supplemental datasets. Table 1 reports the descriptive statistics for paid services. If a doctor does not engage in a particular activity during a given week, the observation for that doctor in that week is recorded as missing. We start by reporting prices for three different types of paid services. For the text/image package 1, the average price is about 92 Yuan.

For the text/image package 2, the average price is about 30 Yuan. Notably, phone call consultations command a higher average price of around 130 Yuan. Regarding the number of consultations, doctors provide 5.1 text/image package 1 consultations, 2.3 text/image package 2 consultations, and 3.4 phone call consultations in a week, on average.

Table 1: Descriptive Statistics of Paid Services

	Obs	Mean	SD	Min	Max
Prices					
Text/Image package 1	173,394	92.29	96.61	5	1,380
Text/Image package 2	73,527	30.33	36.18	2	880
Phone call	103,984	130.21	107.37	1	1,500
Number of Consultations					
Text/Image package 1	173,394	5.14	6.91	0	150
Text/Image package 2	73,527	2.29	2.82	0	52
Phone call	103,984	3.35	5.58	0	99
Quality Measures					
% positive ratings	63,612	0.96	0.17	0	1
Word count of reviews	63,612	13.07	17.27	1	486
Sentiment of reviews	63,612	0.68	0.10	0.27	0.73
Repeat consultations rate	188,649	0.12	0.21	0	1
Word count of doctor messages	128,701	249.85	305.50	1	8,617
Phone call duration (mins)	103,984	7.32	3.30	0.13	21.15
Phone call waiting time (hours)	103,984	4.71	9.57	0.02	100.06

Notes: Summary statistics in this table are based on the two-year doctor-week panel of the 2,229 doctors.

To measure the quality of paid services, we construct four types of metrics, including patient reviews, repeat consultation rate, doctor engagement, and waiting time for consultations. For patient reviews, patients can provide a binary rating – either positive or negative – and a written review post-consultation. On average, 96% of consultations receive positive ratings, with a written review of 13 words and a sentiment score of 0.68 calculated using the Chinese sentiment analysis service provided by Tencent Cloud.[18] For repeat consultation rate, across all types of paid services, 12% of the consultations come from patients who the doctor has seen before. We measure doctor engagement in text/image consultations using the number of words sent by the doctor in a consultation, yielding an average of 249.9

[18]Relevant info can be found at https://cloud.tencent.com/document/product/271/94294.

words. For phone call consultations, we measure doctor engagement by call duration, which averages 7.3 minutes. Finally, the average waiting time is 4.7 hours from booking to phone call consultation. The waiting time for text/image consultations is less relevant because the consultation starts immediately after the doctor accepts the patient's request.

Table 2 reports the descriptive statistics for free services. On average, doctors provide 1.7 free consultations per week.[19] The percentage of positive ratings is 98%, with an average review length of 14 words and a positive sentiment score of 0.68. Repeat consultation rates are not relevant for free services because patients do not have the freedom to choose a doctor. We do not have information on message exchanges in free online services.

Table 2: Descriptive Statistics of Free Services

	Obs	Mean	SD	Min	Max
Number of Consultations					
Free consultations	189,465	1.72	9.69	0	285
Quality Measures					
% positive ratings	10,477	0.98	0.13	0	1
Word counts	10,477	14.43	21.17	1	895
Sentiment	10,477	0.68	0.09	0.27	0.73

Notes: Summary statistics in this table are based on the two-year doctor-week panel of the 2,229 doctors.

Note that our doctor-week panel is unbalanced with varying numbers of observations across variables. This unbalanced nature is due to instances where consultations are not observed for specific doctors in certain weeks. This absence of consultations can be attributed to two reasons: a doctor's unavailability to provide services during a given week or a lack of patient requests for consultations from that doctor. Given this uncertainty and to minimize measurement errors, we retain these values as missing, focusing our analysis on the unbalanced panel data from weeks with at least one observation. To assess the potential impact of missing values on our outcomes, we examine whether missing values at the doctor-service-week level systematically differ between the treated and control groups in pretreatment and posttreatment periods. Our regression analysis, detailed in Web Appendix Table B1, re-

[19] Free online services became available starting from week 20 of 2018. Thus, the number of observations in the doctor-week panel of the number of free online services is 2,229 $\times$ 85 = 189,465.

veals no statistically significant differences between these two groups. This suggests that the patterns of missing values are comparable and, therefore, are unlikely to impact our main results. We further conduct a robustness check when replacing missing values with lagged values for paid service price and with zero for paid service quantity in §6.5, confirming that the main results are consistent.

5 Empirical Strategy

We aim to estimate the causal effects of platform endorsement on market outcomes for newly endorsed doctors. Specifically, we consider both the supply-side and demand-side responses following these leading doctors receiving an endorsement. A natural approach is to use a difference-in-differences (DiD) specification by comparing the changes among endorsed doctors with unendorsed doctors in the treatment period relative to the pretreatment period. The identifying assumption is that, in the absence of platform endorsement, the average outcomes of the endorsed doctors and unendorsed doctors should follow parallel trends. However, this assumption may not hold if there exist time-varying unobserved factors that differ between endorsed and unendorsed doctors.

To account for potential time-varying unobserved factors and strengthen causal identification, we incorporate the concept of synthetic control (Abadie et al., 2010, 2015; Abadie, 2021) and adopt the Generalized Synthetic Control (GSC) method outlined by Xu (2017). The central idea behind synthetic control methods is to use non-treated units to establish a comparable "synthetic control" unit for each treated unit. The synthetic control unit is constructed by using a weighted combination of the non-treated units, where the weights are selected in a way such that they produce a synthetic control that closely mirrors the pretreatment trend of the outcome variable for the treated unit.[20] Once the synthetic control

[20]The reliability of a synthetic control estimator depends on its capacity to consistently follow the trajectory of the outcome variable for the unit impacted prior to the intervention. Thus, it is crucial that the number of pretreatment periods T_0 and control units N_{co} are substantial; i.e., $T_0 > 10$ and $N_{co} > 40$. In our case, we have 53 weeks in the pretreatment period and 2,073 doctors in the control group, which are

is established, its posttreatment trajectory serves as the counterfactual prediction for the treated units. Because this method creates a synthetic control that matches with treated units for the pretreatment pattern of the outcome variable, it inherently accounts for the effects of both *time-varying* observed and unobserved confounders that might otherwise invalidate causal inference. We further account for *time-invariant* confounders, both observed and unobserved, by including doctor fixed effects and service fixed effects. Because of the capability of accounting for unobserved confounders, the synthetic control method has been extensively applied in recent marketing research with quasi-experiments (e.g., Lovett et al., 2019; Pattabhiramaiah et al., 2019; Puranam et al., 2021; Levine and Seiler, 2022). Building upon the standard synthetic control method, the GSC method provides a generalized version by allowing the number of treated units to be more than one, which can accommodate the 156 treated units in our context.

With the GSC method, we use the following specification with interactive fixed effects (Bai, 2009):

$$Y_{it} = \delta_{it} \cdot Endorsed_i \times Post_t + \boldsymbol{\lambda_i'} \boldsymbol{f_t} + \alpha_i + \xi_t + \epsilon_{it}, \tag{1}$$

where Y_{it} represents the outcome of doctor i in week t, such as service price, service quantity, and service quality measures that we will detail later. The term $Endorsed_i$ equals 1 if the doctor was endorsed for the first time in 2019. $Post_t$ equals 1 if the observation is after the week of January 6, 2019, the time when endorsement of "Good Doctor of 2018" was published. δ_{it} represents the treatment effect of platform endorsement of doctor i in week t. $\boldsymbol{f_t}$ is an $r \times 1$ vector representing unobserved factors common across units in week t to be estimated using the control group data, where r is determined by cross-validation. The unobserved factors are weighted by an $r \times 1$ vector of factor loadings $\boldsymbol{\lambda_i}$ specific to doctor i to be estimated using the pretreatment data. The addition of these unobserved factors forms the core of the GSC method, which alleviates the concern of the potential time-varying unobserved factors and thus strengthens causal identification. The detailed

sufficient to generate reliable synthetic control estimators.

estimation steps are provided in Section 3 in Xu (2017). Note that $\boldsymbol{f_t}$ and $\boldsymbol{\lambda_i}$ are estimated individually for each specific outcome variable. We further include additive two-way fixed effects, α_i as doctor fixed effects and ξ_t as week fixed effects, to account for doctors' inherent differences and common temporal shocks to all the doctors, respectively. Lastly, the term ϵ_{it} represents the idiosyncratic error term, which is assumed to be independent of other explanatory variables.

Based on this approach, the average treatment effect on the treated in week t in the post-treatment period, $\widehat{ATT}_t$, for the set of N newly endorsed doctors $\mathcal{T}$, can be calculated based on the average difference between the outcome of a treated doctor $Y_{it}(1)$ and its constructed counterfactual $\hat{Y}_{it}(0)$ (more details on the assumptions and estimation process of $\hat{Y}_{it}(0)$ are provided in Web Appendix C):

$$\widehat{ATT}_t = \frac{1}{N}\sum_{i\in\mathcal{T}}[Y_{it}(1) - \hat{Y}_{it}(0)] = \frac{1}{N}\sum_{i\in\mathcal{T}}\hat{\delta}_{it}, \tag{2}$$

where the standard errors for $\widehat{ATT}_t$ are computed using parametric bootstrapping (details of the inference procedures are provided in Section 3.2 in Xu, 2017).

To check if the GSC approach strengthens the parallel trend, we compare the key outcome variables between the treated group and the constructed synthetic control group in the pretreatment period after applying the GSC approach in Web Appendix Table C2 and Figure C1. We find that the outcomes in the treated group and the synthetic control group are comparable and the parallel trend holds in the pretreatment period with the GSC approach.

In addition to the parallel trend assumption, we also consider the stable unit treatment value assumption (SUTVA); i.e., no spillover of platform endorsement on the control group. A violation of this assumption might occur if, for example, the average unendorsed doctor in our sample faces a significant decrease in patient demand, resulting in estimates being upward biased. However, in our specific study context, the risk of such spillover effects is minimal. This is because less than 0.3% of doctors on the platform have ever received endorsements, leaving more than 99% without any. Consequently, any potential shift in patient demand from unendorsed doctors towards endorsed doctors would likely be spread across thousands of unendorsed doctors, thus diminishing its impact on an average unendorsed doctor. Empirically, we quantify the extent of any possible negative spillover effect on the control group by comparing them to doctors who have been endorsed multiple times. If either a negative spillover on the control group or a positive endorsement effect on multi-time endorsed doctors existed, a significant statistical difference between the two groups would be expected. However, our results show no significant difference, suggesting minimal negative spillover effects on the control group (detailed analysis and discussion in Web Appendix §D). Consequently, we believe that concerns regarding the validity of SUTVA in our study are minimal.

6 Average Effects of Platform Endorsement Among Endorsed Doctors

In this section, we explore the average effects of platform endorsement among endorsed doctors on key market outcomes. Our analysis first focuses on paid services, assessing impacts on both price and quantity. We then examine the endorsement's impact on the provision of free services. After that, we assess the impact of platform endorsement on service quality across several dimensions. Combining these findings, we evaluate the overall impact on service provision by endorsed doctors, further discussing the implications for the platform and the unequal benefits across patients.

6.1 Impact on Paid Service Price

To examine the impact of endorsement on pricing, we estimate the treatment effect on prices set by endorsed doctors. We have detailed price information for three types of paid online services (text/image package 1, text/image package 2, and phone call consultations), all at the doctor-week level. We employ the Generalized Synthetic Control (GSC) approach to account for time-varying unobserved factors. Additionally, we include interacted doctor-service fixed effects to control for time-invariant unobserved factors at the doctor-service level and week fixed effects to account for seasonality.

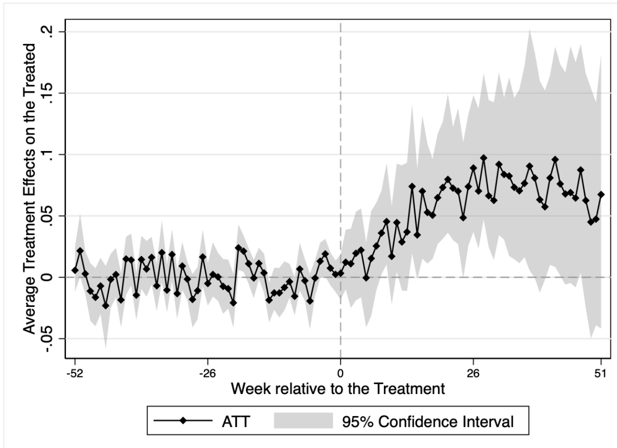


Figure 2: Impact on Paid Consultation Price

Notes: This figure shows the estimated ATT on log(price) and 95% confidence intervals for each week before and after endorsement. We include doctor-service fixed effects and week fixed effects. The standard errors are based on parametric bootstraps of 1,000 times.

Figure 2 presents the estimated average treatment effect on the logged prices among endorsed doctors for each week. Because these effects are estimated at the week level, there are 104 weekly point estimates, represented by black dots. The grey area around these dots indicates the corresponding bootstrapped confidence interval. The dashed vertical line marks the start of the treatment. Pretreatment estimates hovering around zero indicate a good match between the synthetic control doctors and the endorsed doctors, suggesting that the GSC method has adequately accounted for both observed and unobserved attributes to ensure parallel trends. Notably, endorsed doctors gradually raised service prices in the initial six months following endorsement, with prices stabilizing in the subsequent six months. Over the entire posttreatment period, endorsed doctors, on average, increased prices for paid online services by 8.7%** (std. err. = 4.4%). This translates to a price increase from 102 Yuan to 111 Yuan in response to endorsement. This result aligns with existing research demonstrating that platform endorsement or certification can deliver a positive quality signal, leading to a positive price premium for products or services with an endorsement badge in e-commerce markets (e.g. Hui et al., 2016).

6.2 Impact on Paid Service Quantity

Whether platform endorsement increases the provision of paid services by endorsed doctors is ambiguous *a priori* after incorporating doctors' pricing changes. From the patient's perspective, the effect can unfold in either direction. On one hand, an endorsement badge acts as a signal of quality, leading patients to seek more services from endorsed doctors. On the other hand, the higher prices charged by these doctors might drive patients towards unendorsed doctors who offer more affordable services. Similarly, from the doctor's perspective, the effect can manifest in two ways. On one hand, doctors might increase their service provision in response to higher prices. On the other hand, they might reduce the number of services provided because the higher prices enable them to achieve their previous income levels while providing fewer services, especially if they have a predetermined income target (Camerer et al., 1997).

To estimate the effect of platform endorsement on the provision of paid services, we analyze responses from both the demand and supply sides employing the GSC method along with doctor-service and week fixed effects. The process of a paid service involves two steps: a patient initiating a request and a doctor accepting it. Therefore, we first examine the impact of platform endorsement on the number of patient requests, then on doctors' acceptance rates, and finally on the combined effects on the total number of consultations conducted by doctors.

The results for patient requests and doctors' acceptance rates are shown in Web Appendix Figure E1. We observe that endorsed doctors, even after raising their prices, receive a significantly higher number of patient requests following endorsement. Facing this increased demand, endorsed doctors slightly increase their acceptance rates. Figure 3 presents the

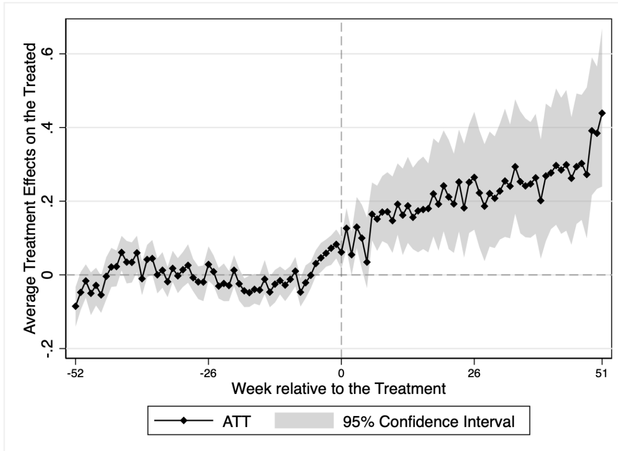


Figure 3: Impact on Paid Service Quantity

Notes: This figure shows the estimated ATT on *log(# consultations + 1)* for paid consultations and 95% confidence intervals for each week before and after endorsement. We include doctor-service fixed effects and week fixed effects in the estimation. The standard errors are based on parametric bootstraps of 1,000 times.

overall impact of platform endorsement on the number of consultations conducted, accounting for both patient demand and doctor acceptance. We find that platform endorsement results in a significant increase of 19.7%*** (std. err. = 7.3%) in the provision of paid services by endorsed doctors, averaged across the three service packages. This corresponds to an increase in the average number of paid consultations per week for an endorsed doctor from 27.2 to 32.6.

These findings regarding the quantity of paid services have two implications. First, on the patient side, it is evident that platform endorsement serves as a strong quality signal because the number of patient requests increases significantly despite notable price hikes. Second, on the doctor side, platform endorsement effectively motivates these leading providers to expand their provision of paid services. This is seen in their increased number of consultations and higher acceptance rates of patient requests. This finding suggests that these leading doctors do not seem to be constrained by a fixed income target, but rather are motivated by the increased financial benefits presented by platform endorsement.

6.3 Impact on Free Service Quantity

Paid services are important to the platform's profitability. At the same time, free services are valued for their role in building a corporate social responsibility image (Plewa et al., 2015), enhancing brand equity (Wang et al., 2015), and supporting long-term growth (Deng et al., 2023; Liu et al., 2014). Furthermore, the provision of free services offers significant benefits to underprivileged patients and is a critical element in improving healthcare equity (Yates, 2009). This section aims to assess the impact of platform endorsement on the quantity of free services provided by endorsed doctors.

In contrast to paid services, where both patient requests and doctors' acceptances affect service quantity, free service quantity reflects changes *only* from the supply side. This difference arises for two reasons: First, in free services, patients do not have the option to choose their doctors; instead, it is up to the doctors to decide whether to pick up a request for free service. Second, given that the demand for free services far exceeds the supply,[21] any increase or decrease in the provision of free services by endorsed doctors is unlikely to be offset by other doctors' free service provision.

In theory, the effect of platform endorsement on the quantity of free services remains ambiguous *a priori*. On one hand, previous studies indicate that status signaling, similar to endorsement, could incentivize health workers to conduct more volunteer work (Fracchia et al., 2023). On the other hand, there is a possibility that an increase in paid service provision may substitute the time doctors would otherwise allocate to free services, potentially leading to a decrease in the quantity of free services offered.

Figure 4 presents the estimated effect of endorsement on the provision of free services by endorsed doctors. The result indicates that platform endorsement leads to a significant decrease in the number of free services by endorsed doctors. Over the entire treatment year, the average ATT is $-35.2\%^{***}$ (std. err. $= 10.3\%$) for free services, corresponding to a

[21] Patient requests for free services is at least 1.5 times the number of free consultations that doctors provide.

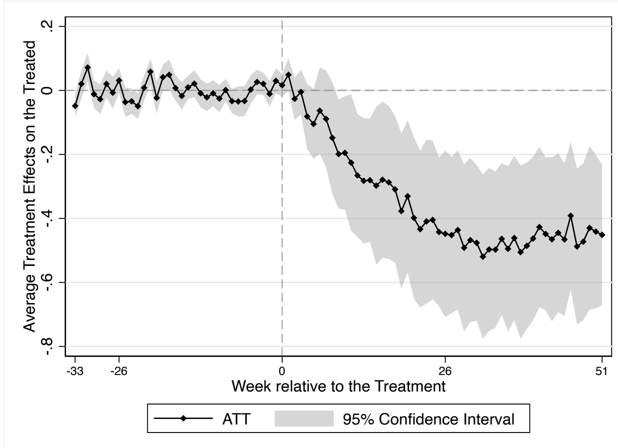


Figure 4: Impact on Free Service Quantity

Notes: This figure shows the estimated ATT on *log(# consultations+1)* for free consultations and 95% confidence intervals for each week before and after endorsement. We include doctor fixed effects and week fixed effects in the estimation. The standard errors are based on parametric bootstraps of 1,000 times.

decline in weekly consultations from 9.4 to 6.1 by an average endorsed doctor. This trend suggests that platform endorsement, though unintentional, negatively affects the availability of free services via the platform, potentially disadvantaging underprivileged patients.

6.4 Impact on Service Quality

Quality has been documented as one of the most important attributes that affect consumers' purchasing decisions and a supplier's success (Golder et al., 2012; Tellis and Johnson, 2007). This attribute assumes even greater significance in the context of healthcare services. In contrast to product markets where quality typically remains fixed, quality in service markets, particularly in online doctor consultations, is endogenously determined by doctors and can vary over time. Consequently, it can be significantly influenced by information disclosure tools, such as platform endorsement.

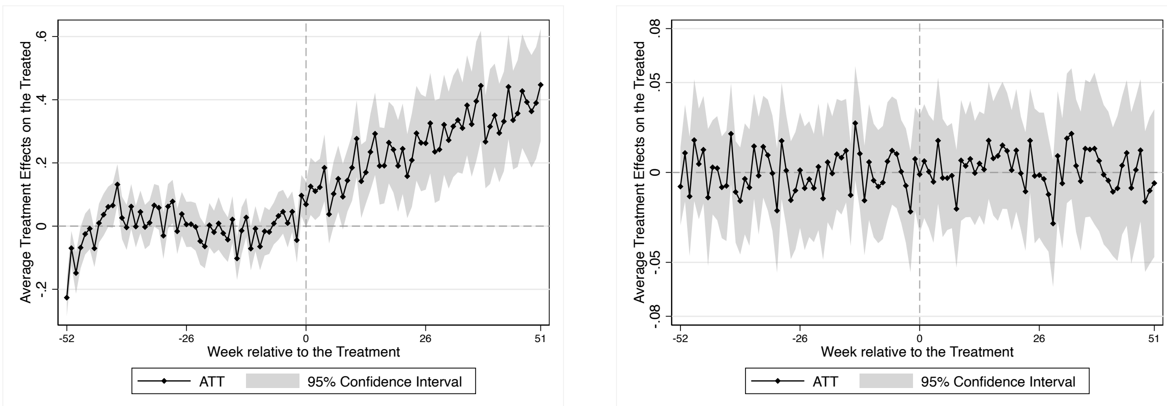
The impact of platform endorsement on quality could go either direction. Endorsed doctors may improve the quality of their services to maintain the higher recognition they receive from the platform and the larger community. Conversely, an increase in the quantity of consultations, a result of platform endorsement, may compel doctors to reduce service quality.

This potential decline stems from allocating less time and effort per patient, exemplifying the previously documented trade-off between quality and quantity in healthcare (Grieco and McDevitt, 2017).

Measuring the quality of healthcare services presents a significant challenge. Upadhyai et al. (2019) conduct a comprehensive review of 124 healthcare papers and conclude that healthcare service quality measurement lacks a standard approach and must be tailored to specific contexts. In online healthcare, where consultations primarily offer expert advice and second opinions without direct treatment, final healthcare outcomes are not readily available. Therefore, we evaluate the quality of online healthcare services using four dimensions: patient reviews, repeat consultation rate, doctor engagement, and waiting time. These dimensions have been chosen because they capture both patient satisfaction and doctors' service attributes, which collectively offer a comprehensive evaluation of the service quality provided.

Patient Reviews: Online reviews are a reliable way to learn about quality, as demonstrated by Tellis and Johnson (2007) and Lantzy et al. (2021). Thus, we first use patient reviews as a measure for service quality. Specifically, we extract three metrics from the patient reviews: the ratio of positive ratings in reviews, the average word count of reviews, and the average sentiment score of reviews at the doctor-week level. Across these three metrics, we do not find any statistically significant effects as a result of platform endorsement (see results in Web Appendix G1). The primary reason behind this is likely to be the limited variation in patient reviews because 96% of them are positive and patients can select review statements from a predetermined list prepared by the platform.

Repeat Consultations: Service quality has been identified as a strong driver behind repeat purchases (Boulding et al., 1993; Zeithaml et al., 1996). Accordingly, we use repeat consultations as the second measure of quality. In our context, choosing the same doctor for subsequent consultations implies greater patient satisfaction for three main reasons. First, switching doctors after an unsatisfied consultation online is easy, making repeat consultations a strong indicator of satisfaction. Second, since endorsed doctors typically charge higher fees for paid services, patients' willingness to pay more to see these doctors again underscores their satisfaction. Lastly, it is important to differentiate between repeat consultations in online healthcare and hospital readmissions. The former signals satisfaction in seeking expert advice, while the latter is often associated with negative outcomes of a previous treatment.



(a) # of Repeat Consultations

(b) Repeat Consultation Rate

Figure 5: Impact on Repeat Consultations

Notes: These figures show the estimated ATT on *log(# repeat consultations + 1)* and repeat consultation rate, along with 95% confidence intervals for each week before and after endorsement. We include both doctor fixed effects and week fixed effects. The standard errors are based on parametric bootstraps of 1,000 times.

We assess repeat consultations at the doctor-week level in terms of both their number and rate. The number of repeat consultations is defined as the number of paid consultations conducted by patients who have previously seen the same doctor. The repeat consultation rate is the ratio of these repeat consultations to the total number of paid consultations.[22] As presented in Figure 5, the left panel shows that an average endorsed doctor observes a 23.2%*** (std. err. = 3.8%) increase in repeat consultations, rising from 1.91 to 2.35 per week. However, considering that these endorsed doctors also conduct more consultations overall, we further estimate the impact on repeat consultation rate and find the effect is insignificant (ATT = 0.002, std. err. = 0.003), as shown in the right panel. Combining

[22]This analysis is limited to paid consultations because in free consultations patients cannot select their desired doctors, making repeat consultations less relevant.

these findings, we conclude that these leading doctors are able to maintain their service quality after endorsement.

Doctor Engagement: In addition to patient reviews and repeat consultations, we further collect objective measures of consultation attributes. Specifically, using the unique data on messages exchanged between doctors and patients in text/image consultations, we calculate the level of doctor engagement, measured by the number of words from doctors within a consultation.

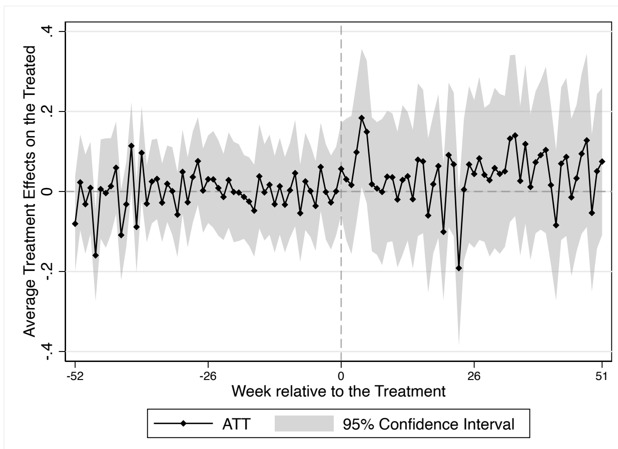


Figure 6: Impact on Word Count of Doctors' Replies

Notes: This figure shows the estimated ATT on *log(word count of doctors' replies)* for text/image consultations and 95% confidence intervals for each week before and after endorsement. We include both doctor fixed effects and week fixed effects. The standard errors are based on parametric bootstraps of 1,000 times.

Figure 6 presents the estimated weekly ATT on the logged word count of doctors' replies within a consultation. We find that the word count of doctors' replies after endorsement increases by about 9.6%*** (std. err. = 3.6%), from 275.4 to 301.8 words, suggesting that endorsed doctors seem to increase their engagement in text/image consultations, which constitute the primary service type (76.8%) in paid online services.

Apart from service attributes in the text/image consultations, we also have duration data for phone call consultations, which serve as another proxy for doctor engagement. We find no statistically significant changes in phone call duration before and after endorsement (see results in Web Appendix Figure G2).

Waiting Time: The final quality measure we use is the waiting time for phone call consultations, calculated from the booking to the consultation initiation time. Our analysis does not show any significant changes in waiting time for phone call consultations in response to endorsement (see Web Appendix Figure G3). The waiting time for text/image consultations is less relevant because the consultation starts immediately after the doctor accepts the patient's request.

Considering the outcomes across the four quality metrics — patient reviews, repeat consultations, doctor engagement, and waiting time — we conclude that endorsed doctors are able to maintain their service quality even as they increase the quantity of services provided on the platform. This is evidenced by increased number of repeat consultations and doctor engagement and no negative impact on patient reviews, repeat consultation rate or waiting time.

6.5 Robustness

To test the robustness of our results, we conduct four sets of additional analyses.

Missing Values: As discussed in the Data section §4, missing values in certain variables may arise due to two reasons: a doctor's unavailability to provide service during a given week or a lack of patient requests for consultations from that doctor in a given week. To minimize measurement errors, we retain these values as missing for the main analyses. However, to assess the robustness of our main results, we conduct an additional analysis where missing values are replaced with lagged values for paid service price and with zero for paid service quantity. The underlying rationale for this replacement and the implementation process are detailed in Web Appendix §F. The results, reported in Web Appendix Table F1 and Table F2, corroborate the findings of our main analysis, demonstrating consistency in both economic and statistical significance. Note that we do not have the missing value issue for free services because the free service quantity accurately reflects the supply side provision.

Difference-in-Differences (DiD): To assess the robustness of our main findings, we employ the standard DiD method as an alternative approach. DiD offers the advantage of simplicity and is free from any weighting or matching process. However, unlike the GSC method, DiD does not account for the potential existence of time-varying unobserved factors that differ between endorsed and control doctors. Despite this limitation, we present the results from the DiD method in Web Appendix Table F3. We find that while the estimated effects are smaller compared to those obtained using the GSC approach, the key findings remain consistent in terms of both directional alignment and statistical significance.

Propsensity Score Matching with Difference-in-Differences (PSM-DiD): PSM-DiD presents an alternative approach to the GSC method. Unlike GSC, which accounts for unobserved factors by creating synthetic versions of the treated units, PSM-DiD finds a matched control for a treated unit based on observed factors. As a result, the validity of PSM-DiD relies on the uncounfoundedness assumption, where no observed factors are correlated with the treatment, conditional on the observed variables (Arkhangelsky and Imbens, 2023). Assuming that the unconfoundedness assumption holds, the estimates obtained through PSM-DiD remain consistent. The results of the PSM-DiD analysis are detailed in Web Appendix Table F4, which again demonstrate consistency.

Alternative Functional Form: Instead of using logarithmic transformation, we assess the robustness of our findings on price and quantity with the absolute measures. The results are consistent and presented in Web Appendix Table F5.

6.6 Implications of the Impact of Platform Endorsement

So far we have found that platform endorsement has significant impacts on paid service price and quantity of both paid and free services and has minimal impact on service quality at the doctor level. To gain a comprehensive understanding of platform endorsement, we now discuss the implications of the aggregate impact on service provision for doctors, patients, and the platform.

According to estimates from §6.2 and §6.3, we see that before endorsement, an endorsed doctor on average provides 27.2 paid services and 9.4 free services, and after endorsement, an endorsed doctor on average increases paid services to 32.6 while decreases free services to 6.1 per week. Adding paid and free services, the total weekly number of services for an endorsed doctor increases from 36.8 to 38.7; i.e., a 5.2% increase. The increase in paid services gives an endorsed doctor an additional 6,971 USD annually from the platform, roughly half the average annual salary of a full-time doctor in China.[23] At the same time, this increase in total service provision by endorsed doctors positively contributes to the platform's revenue.[24]

Despite the revenue increase, the endorsement program has resulted in about 27,000 fewer free consultations offered by these leading doctors in China, translating to approximately half a million US dollars benefit loss for underprivileged patients.[25] It is important to note that this reduction in free consultations is unlikely to be compensated by unendorsed doctors given that the demand for free services consistently exceeds the supply both before and after endorsement. This benefit loss is equivalent to about 710 times the annual income threshold for China's subsistence allowance recipients.[26] This decrease in free consultations could have significant consequences for the platform. First, the reduction in free services could limit their positive spillover on paid services and thus slow down the platform's overall growth in the long term (Deng et al., 2023; Liu et al., 2014). Second, considering the Chinese

[23] An average doctor's revenue before endorsement is calculated as 27.2 services/week $\times$ 52 weeks $\times$ 101 Yuan/service = 142,854.4 Yuan. An average doctor's revenue after endorsement is calculated as 32.6 services/week $\times$ 52 weeks $\times$ 111 Yuan/service = 188,167.2 Yuan. The difference between the two is = 45,312.8 Yuan $\approx$ 6,971 USD. We use the average exchange rate of 6.5 CNY to 1 USD for the year 2019 throughout the paper. Source of the average annual salary of a full-time doctor in China: https://www.sohu.com/a/452654912_668211.

[24] Without data on patients' options outside of the platform, we cannot provide a precise estimate on the revenue increase for the platform. If the additional services provided by endorsed doctors are due to market expansion, then the net revenue increase for the platform would be about $1.1 million annually (6,971 USD $\times$ 156 endorsed doctors), the equivalent to the annual pay of 80 full-time employed doctors in China. However, if these services merely substitute those provided by unendorsed doctors, then the estimated revenue increase should be considered only as an upper bound.

[25] An endorsed doctor on average conducted 3.3 fewer free consultations per week after endorsement. With 156 newly endorsed doctors, the reduction in free consultations is 3.3 consultations per doctor per week $\times$ 52 weeks $\times$ 156 doctors = 26,770 consultations. To get this number of consultations from endorsed doctors if the patients had paid for the services, the cost equals 26,770 consultations $\times$ 111 Yuan/consultation = 3 million Yuan $\approx$ 0.5 million USD.

[26] The median annual income threshold for recipients of China's subsistence allowance recipients is about 4200 Yuan, equivalent to 650 USD. Source: https://www.sohu.com/a/323488271_120065118.

government's extensive efforts to provide free medical consultations to the underprivileged, as well as increasingly stringent requirements for CSR reporting, the reduction in free services on the platform — particularly those offered by reputable leading doctors — could negatively impact the platform's CSR image and brand equity.

7 Heterogeneous Effects Across Doctors

Our analysis reveals that information disclosure via platform endorsement yields a concerning downside: a negative impact on the provision of free services, which hurts underprivileged patients and could undermine the platform's corporate social responsibility image and, by extension, its brand equity and long-term growth. The reduction of free services is concerning for both the platform and society. To better understand this reduction, we explore the heterogeneous effects across doctors as a result of information disclosure through platform endorsement. To mitigate this issue and to optimize information disclosure design, a deeper understanding of the reduction in free services is essential. We investigate how the influence of platform endorsement differs among doctors.

We categorize doctors into two groups: "pro-social doctors" and "non-pro-social doctors" based on their relative provision of free services compared to the median during the pretreatment period. This categorization is based on doctors' observed pro-social activities instead of their unobserved motives behind these activities. The true motives could be either pure altruism (Galizzi et al., 2023)—where doctors genuinely care about the welfare of underprivileged patients—or impure altruism—where doctors provide free services in hopes of gaining reputation (Berman and Silver, 2022). Regardless of the underlying motives, the platform's objective is to ensure that endorsement does not discourage these pro-social activities. We present summary statistics of the two groups of doctors who have received endorsement in Web Appendix H1. The two groups differ in their free service provision and paid service prices, but exhibit similarities across all other key attributes including paid service quantity, gender, age, professional title, education, tenure on the platform, department, and location.

Table 3 presents the impact of endorsement on the two groups separately. The estimates reveal contrasting behaviors. Pro-social doctors, upon receiving endorsement, generally refrain from raising their prices for paid services. This minimal price increase, coupled with the positive quality signal from endorsement, leads to a significant rise in the demand and provision of paid services. However, due to capacity constraints, this increase in paid services results in a significant decrease in free services offered by the pro-social doctors. In contrast, non-pro-social doctors, following endorsement, raise their service prices by approximately 16%. This substantial increase limits the growth in demand for their paid services and consequently does not affect their provision of free services much. We further corroborate these findings by measuring doctors' pro-social levels with a continuous measure based on doctors' share of free service provision among all services delivered during the pretreatment period. We then conduct regression analyses to see how this continuous pro-social measure is correlated with our estimated ATTs of endorsement on paid service price, paid service quantity, and free service quantity, respectively. The results are presented in Web Appendix Table H2. Consistently, our analysis indicates that doctors with higher pro-social levels tend to increase their paid service prices less and conduct a greater number of paid services, but at the expense of offering fewer free services.

Table 3: Heterogeneous Effects on Pro-Social and Non-Pro-Social Doctors

	Paid Services				Free Services	
	log(Price)		log(Quantity)		log(Quantity)	
	Pro-Social	Non-Pro-Social	Pro-Social	Non-Pro-Social	Pro-Social	Non-Pro-Social
ATT	-0.008	0.161*	0.227**	0.183	-0.612***	-0.079
	(0.060)	(0.061)	(0.103)	(0.095)	(0.139)	(0.136)

Notes: The ATT for each subgroup is calculated by averaging the estimated individual treatment effect δ_{it} from the GSC method, as shown in equation (1), across each subgroup. The standard errors in parentheses are based on parametric bootstraps of 1,000 times. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

These findings are crucial for the information disclosure design of online healthcare platforms. Initially, one might naively assume that endorsement would have a positive impact on pro-social doctors by encouraging them to increase free service provision. Contrarily, our study reveals that the reduction in free services is mainly driven by the impact of endorsement on pro-social doctors. Because these doctors are hesitant to raise paid service prices, they experience a surge in paid service demand, which negatively affects their capacity to offer free services, adversely impacting underprivileged patients. This underscores the importance of online healthcare platforms carefully considering the potential unintended consequences of information disclosure, not only on doctors' pricing decisions but also on their choices regarding the balance between free and paid services. In response, these platforms could consider introducing an alternative endorsement program that recognizes and encourages doctors' pro-social commitment to providing free services by placing greater weight on the free service provision in the selection criteria.

8 Conclusion

As an increasing number of doctors participate in online platforms, an unprecedented number of choices has become available to patients who seek online healthcare services, which amplifies the persistent challenge of information asymmetry in the healthcare sector. To address this issue, platform endorsement, where online platforms endorse a select set of high-quality doctors, has become popular in online healthcare platforms to signal leading doctors' quality, facilitate patients' decision making, and encourage leading doctors to improve their practices. To evaluate the impact of platform endorsement, we analyze its effect on various market outcomes, including service price, quantity, service type between paid and free services, and service quality.

Focusing on a leading online healthcare consultation platform in China, we analyze its "Good Doctor of the Year" endorsement program. Using a weekly panel of 2,229 doctors spanning two years, we find that platform endorsement, serving as a positive quality signal, leads to increased demand for endorsed doctors, prompting them to raise paid service prices and expand paid service provision. However, one downside of platform endorsement is that it leads endorsed doctors to reduce their provision of free services, which predominantly hurts underprivileged patients, worsens healthcare inequality, and could also inadvertently affect the platform's brand equity and long-term growth. We further find that this reduction in free services is more pronounced among endorsed doctors who engage in more pro-social behaviors during the pretreatment period. Turning to service quality, we find that doctors are able to maintain their consultation quality following endorsement, evidenced by increased doctor engagement and no negative impact on patient reviews, repeat consultation rate, or waiting time.

These findings are important for understanding the role of platform endorsement in online healthcare. When designing information disclosure, it is essential to carefully consider not just the impact on service price and quantity, but also service quality, which directly impacts patient welfare. Furthermore, it is important to acknowledge that the positive quality signal from information disclosure may lead to unintended congestion among leading doctors, potentially causing a reallocation of their services. This understanding necessitates a nuanced assessment of the differential impacts of free versus paid services, which yield significantly different benefits for various patient groups. Therefore, adopting a comprehensive approach to evaluate the impact of platform endorsement can guide platforms and policymakers in addressing the diverse needs of patients. This will enhance healthcare access and equity, ultimately leading to higher social welfare.

There are, of course, limitations to our study. First, our study centers on a leading online doctor consultation platform in China. The magnitude of the impact of platform endorsement might vary if the criteria for endorsement or the proportion of endorsed doctors differ in other settings. However, our key insight — that there is a need for a comprehensive understanding of information disclosure tools in the healthcare sector where doctors must make complex decisions — still holds for both platforms and policymakers. Second, because our sample is restricted to the very best and most active doctors on the platform, the impact of platform endorsement on the long tail of doctors cannot be studied with the data we have. Third, in our context, doctors must maintain full-time positions at offline hospitals, limiting the impact of online information disclosure on their offline service provision. However, in contexts where doctors have the flexibility to allocate their time between online and offline service provision, examining the interplay between these two modes of healthcare delivery could yield insightful findings. We acknowledge these gaps and leave them for future research.

References

Abadie, Alberto (2021) "Using synthetic controls: Feasibility, data requirements, and methodological aspects," *Journal of Economic Literature*, 59 (2), 391–425.

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller (2010) "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program," *Journal of the American Statistical Association*, 105 (490), 493–505.

——— (2015) "Comparative politics and the synthetic control method," *American Journal of Political Science*, 59 (2), 495–510.

Arkhangelsky, Dmitry and Guido Imbens (2023) "Causal models for longitudinal and panel data: A survey,"Technical report, National Bureau of Economic Research.

Arrow, Kenneth J. (1963) "Uncertainty and the welfare economics of Medical Care," *The American Economic Review*, 53 (5), 941–973.

Avdic, Daniel, Giuseppe Moscelli, Adam Pilny, and Ieva Sriubaite (2019) "Subjective and objective quality and choice of hospital: Evidence from maternal care services in Germany," *Journal of Health Economics*, 68, 102229.

Bai, Jushan (2009) "Panel data models with interactive fixed effects," *Econometrica*, 77 (4), 1229–1279.

Bairathi, Mimansa, Xu Zhang, and Anja Lambrecht (2022) "The value of platform endorsement," Working paper.

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

Berman, Jonathan Z and Ike Silver (2022) "Prosocial behavior and reputation: When does doing good lead to looking good?" *Current Opinion in Psychology*, 43, 102–107.

Boulding, William, Ajay Kalra, Richard Staelin, and Valarie A Zeithaml (1993) "A dynamic process model of service quality: from expectations to behavioral intentions," *Journal of Marketing Research*, 30 (1), 7–27.

Brown, Zach Y, Christopher Hansman, Jordan Keener, and Andre F Veiga (2023) "Information and disparities in health care quality: Evidence from GP Choice in England," Working paper.

Burtch, Gordon, Qinglai He, Yili Hong, and Dokyun Lee (2022) "How do peer awards motivate creative content? Experimental evidence from Reddit," *Management Science*, 68 (5), 3488–3506.

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler (1997) "Labor supply of New York City cabdrivers: One day at a time," *The Quarterly Journal of Economics*, 112 (2), 407–441.

Chen, Yiwei and Stephanie Lee (2024) "User-generated physician ratings and their effects on patients' physician choices: Evidence from Yelp," *Journal of Marketing*, 88 (1), 77–96.

Cheng, Terence C, Hongqiao Fu, Duo Xu, and Winnie Yip (2022) "Technology platforms are revolutionizing health care service delivery in China," *NEJM Catalyst Innovations in Care Delivery*, 3 (1).

Cutler, David M, Robert S Huckman, and Mary Beth Landrum (2004) "The role of information in medical markets: An analysis of publicly reported outcomes in cardiac surgery," *American Economic Review*, 94 (2), 342–346.

Deng, Yiting, Anja Lambrecht, and Yongdong Liu (2023) "Spillover effects and freemium strategy in the mobile app market," *Management Science*, 69 (9), 5018–5041.

Dewan, Sanjeev, Jooho Kim, and Tingting Nian (2023) "Economic impact of platform-endorsed quality certification: Evidence from Airbnb," *MIS Quarterly*, 47 (3).

Dranove, David, Daniel Kessler, Mark McClellan, and Mark Satterthwaite (2003) "Is more information better? The effects of "report cards" on health care providers," *Journal of Political*

Economy, 111 (3), 555–588.

Elfenbein, Daniel W, Raymond Fisman, and Brian McManus (2015) "Market structure, reputation, and the value of quality certification," *American Economic Journal: Microeconomics*, 7 (4), 83–108.

Fracchia, Mattia, Teresa Molina-Millán, and Pedro C Vicente (2023) "Motivating volunteer health workers in an african capital city," *Journal of Development Economics*, 163, 103096.

Galizzi, Matteo M, Geir Godager, Jing Li, Ismo Linnosmaa, Timo Tammi, and Daniel Wiesen (2023) "Economics of Healthcare Provider Altruism," *Handbook of Labor, Human Resources and Population Economics', Springer Cham.*

Gallus, Jana (2017) "Fostering public good contributions with symbolic awards: A large-scale natural field experiment at Wikipedia," *Management Science*, 63 (12), 3999–4015.

Golder, Peter N, Debanjan Mitra, and Christine Moorman (2012) "What is quality? An integrative framework of processes and states," *Journal of Marketing*, 76 (4), 1–23.

Grieco, Paul LE and Ryan C McDevitt (2017) "Productivity and quality in health care: Evidence from the dialysis industry," *The Review of Economic Studies*, 84 (3), 1071–1105.

Guo, Tong, S Sriram, and Puneet Manchanda (2020) ""Let the sunshine in": The impact of industry payment disclosure on physician prescription behavior," *Marketing Science*, 39 (3), 516–539.

Gutacker, Nils, Luigi Siciliani, Giuseppe Moscelli, and Hugh Gravelle (2016) "Choice of hospital: Which type of quality matters?" *Journal of Health Economics*, 50, 230–246.

Huang, Justin, Rupali Kaul, and Sridhar Narayanan (2022) "Variety and Risk-Taking in Content Creation: Evidence from a Field Experiment Using Image Recognition Techniques," Working paper.

Huang, Justin T and Sridhar Narayanan (2020) "Effects of attention and recognition on engagement, content creation and sharing: Experimental evidence from an image sharing social network," Working paper.

Hui, Xiang, Maryam Saeedi, Zeqian Shen, and Neel Sundaresan (2016) "Reputation and regulations: Evidence from eBay," *Management Science*, 62 (12), 3604–3616.

Lantzy, Shannon, Rebecca W Hamilton, Yu-Jen Chen, and Katherine Stewart (2021) "Online reviews of credence service providers: What do consumers evaluate, do other consumers believe the reviews, and are interventions needed?" *Journal of Public Policy & Marketing*, 40 (1), 27–44.

Levine, Julia and Stephan Seiler (2022) "Identifying state dependence in brand choice: Evidence from hurricanes," *Marketing Science*.

Liu, Charles Zhechao, Yoris A Au, and Hoon Seok Choi (2014) "Effects of freemium strategy in the mobile app market: An empirical study of google play," *Journal of Management Information Systems*, 31 (3), 326–354.

Lovett, Mitchell J, Renana Peres, and Linli Xu (2019) "Can your advertising really buy earned impressions? The effect of brand advertising on word of mouth," *Quantitative Marketing and Economics*, 17, 215–255.

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

Lu, Susan Feng (2012) "Multitasking, information disclosure, and product quality: Evidence from nursing homes," *Journal of Economics & Management Strategy*, 21 (3), 673–705.

Luca, Michael and Sonal Vats (2013) "Digitizing doctor demand: The impact of online reviews on doctor choice," *Cambridge, MA: Harvard Business School.*

Michelson, Joan (2019) "Why Your Company's Social Responsibility Metrics Matter And How To Get Them," *Forbes*.

Noronha, Carlos, Si Tou, MI Cynthia, and Jenny J Guan (2013) "Corporate social responsibility reporting in China: An overview and comparison with major trends," *Corporate Social Responsibility and Environmental Management*, 20 (1), 29–42.

Pattabhiramaiah, Adithya, S Sriram, and Puneet Manchanda (2019) "Paywalls: Monetizing online content," *Journal of Marketing*, 83 (2), 19–36.

Plewa, Carolin, Jodie Conduit, Pascale G Quester, and Claire Johnson (2015) "The impact of corporate volunteering on CSR image: A consumer perspective," *Journal of Business Ethics*, 127, 643–659.

Puranam, Dinesh, Vrinda Kadiyali, and Vishal Narayan (2021) "The impact of increase in minimum wages on consumer perceptions of service: A transformer model of online restaurant reviews," *Marketing Science*, 40 (5), 985–1004.

Santos, Rita, Hugh Gravelle, and Carol Propper (2017) "Does quality affect patients' choice of doctor? Evidence from England," *The Economic Journal*, 127 (600), 445–494.

Tellis, Gerard J and Joseph Johnson (2007) "The value of quality," *Marketing Science*, 26 (6), 758–773.

Upadhyai, Raghav, Arvind Kumar Jain, Hiranmoy Roy, and Vimal Pant (2019) "A review of healthcare service quality dimensions and their measurement," *Journal of Health Management*, 21 (1), 102–127.

Wang, David Han-Min, Pei-Hua Chen, Tiffany Hui-Kuang Yu, and Chih-Yi Hsiao (2015) "The effects of corporate social responsibility on brand equity and firm performance," *Journal of Business Research*, 68 (11), 2232–2236.

Werner, Rachel M and David A Asch (2005) "The unintended consequences of publicly reporting quality information," *JAMA*, 293 (10), 1239–1244.

WHO (2010) *Telemedicine: opportunities and developments in member states. Report on the second global survey on eHealth*: World Health Organization.

Xu, Yiqing (2017) "Generalized synthetic control method: Causal inference with interactive fixed effects models," *Political Analysis*, 25 (1), 57–76.

Xu, Yuqian, Mor Armony, and Anindya Ghose (2021) "The interplay between online reviews and physician demand: An empirical investigation," *Management Science*, 67 (12), 7344–7361.

Yates, Rob (2009) "Universal health care and the removal of user fees," *The lancet*, 373 (9680), 2078–2081.

Yoon, Tae Jung (2020) "Quality information disclosure and patient reallocation in the healthcare industry: Evidence from cardiac surgery report cards," *Marketing Science*, 39 (3), 636–662.

Zeithaml, Valarie A, Leonard L Berry, and Ananthanarayanan Parasuraman (1996) "The behavioral consequences of service quality," *Journal of Marketing*, 60 (2), 31–46.

Web Appendix

A More Details of the Platform

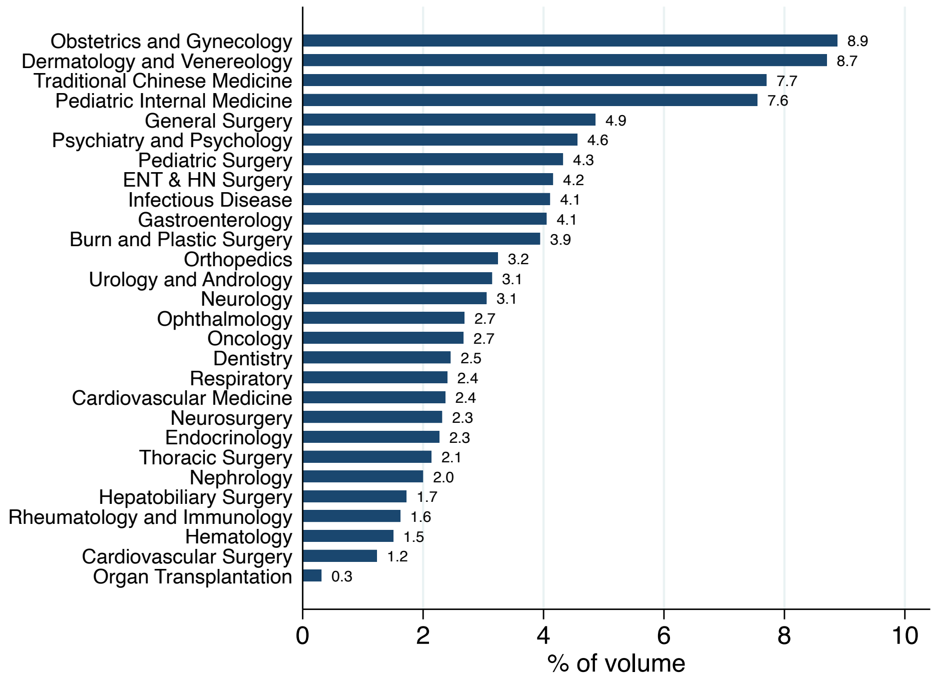


Figure A1: Distribution of Service Volume Across Departments

Notes: The numbers are calculated based on the online consultations in our sample in 2018–2019.

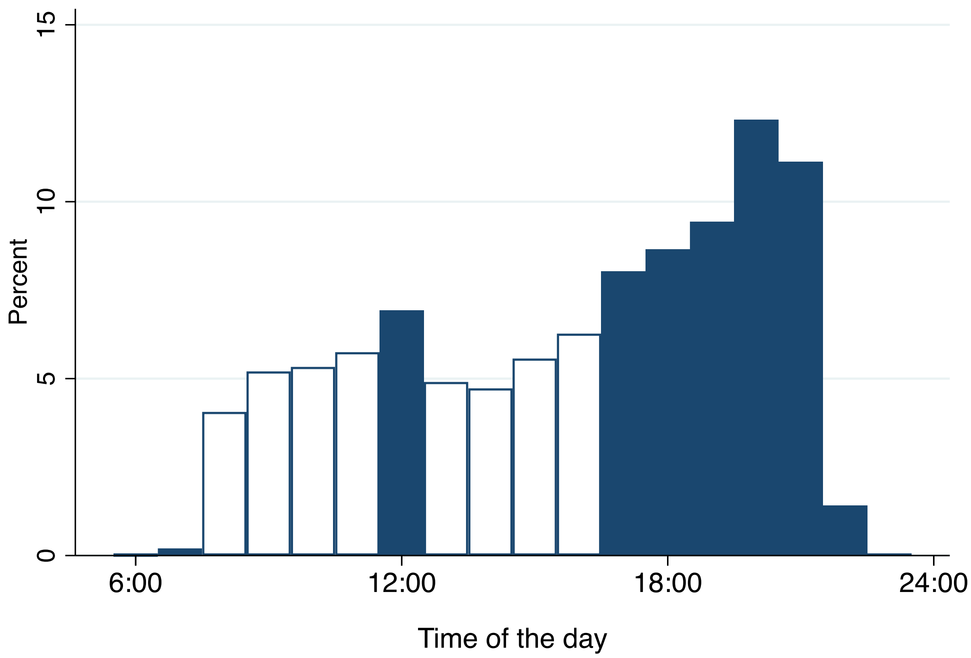


Figure A2: Distribution of Service Time for Phone Call Consultations

Notes: Distribution of hours during which doctors engage in phone call consultations. The percentages are calculated from the phone call consultations of our doctor sample from 2018 to 2019. The solid bars represent lunch breaks and after-hours. In total, more than 50% of consultations take place during those times.

B Analysis on the Missing Value Pattern in Paid Online Services

In our main analysis, we focus on the unbalanced panel data with weeks having at least one observation. To assess the potential impact of missing values on the findings, we examine whether the occurrence of missing values at the doctor-service-week level systematically differs between the treated and control groups after the treatment. The results of both the difference-in-difference method and the generalized synthetic control method are reported in Table B1. We find no statistically significant differences in the occurrence of missing values between the two groups after the treatment. This suggests that the patterns of missing values are comparable, implying endorsement do not seem to affect the number of weeks that a doctor provides consultations on the platform. Therefore, missing values are unlikely to affect our main results.

Table B1: Missing Values Incidence on Paid Online Consultations

	$\mathbb{1}$(no requests in a week)	
	(1) DID	(2) GSC
ATT	-0.008	-0.018
	(0.014)	(0.028)

Notes: Doctor-service fixed effects and week fixed effects are included. Standard errors are reported in parentheses. In Column (1), standard errors are clustered at the doctor level. In Column (2), standard errors are based on parametric bootstraps of 1,000 times. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

C Details on the Generalized Synthetic Control Method

C.1 Assumptions of the GSC method

The GSC method creates synthetic control units that incorporate unobserved common factors that affect both treated and control units to ensure parallel trends. This method assumes that the treated units and control units are affected by the same set of unobserved factors during the sample period. To make casual interpretations of δ_{it}, we further need several assumptions regarding the error term. First, the error term of any doctor at any week needs to be independent of the treatment assignment ($Endorsed_i \times Post_t$), conditional on doctor and week fixed effects (α_i and ξ_t), and unobserved cross-sectional and temporal heterogeneities ($\boldsymbol{f_t}$ and $\boldsymbol{\lambda_i}$) of all doctors. Second, the GSC method requires weak serial dependence of error terms and a set of (standard) regularity conditions. Third, it requires error terms to be cross-sectionally independent and homoscedastic for valid inference based on a block bootstrap procedure. These assumptions regarding the error terms are standard in the literature.

C.2 Estimation of the counterfactual outcome of each endorsed doctor $Y_{it}(0)$

Estimation of $Y_{it}(0)$ proceeds in three steps:

1. We exclusively use data of unendorsed doctors to estimate α_i, ξ_t, $\boldsymbol{f_t}$, and $\boldsymbol{\lambda_i}$ for all control units.

2. Given estimates $\hat{\xi}_t$ and $\boldsymbol{\hat{f}_t}$, we use pretreatment period data for all endorsed doctors to estimate α_i and factor loadings $\boldsymbol{\lambda_i}$ for these doctors by minimizing the mean squared error of the predicted outcome of treated doctors in pretreatment periods.

3. We construct a synthetic control doctor for each endorsed doctor by applying the estimates of $\hat{\xi}_t$ and $\boldsymbol{\hat{f}_t}$ from the first step and the estimated $\hat{\alpha}_i$ and factor loadings $\boldsymbol{\hat{\lambda}_i}$ for endorsed doctors from the second step and plugging them into the interactive fixed effect model: $\hat{Y}_{it}(0) = \boldsymbol{\hat{\lambda}_i'}\boldsymbol{\hat{f}_t} + \hat{\alpha}_i + \hat{\xi}_t$, where $\hat{Y}_{it}(0)$ denotes the counterfactual outcome for endorsed doctor i in week t in the absence of endorsement.

C.3 Pretreatment Summary Statistics

With the raw data, we first present summary statistics of key outcome variables of the endorsed group and the control group during the pretreatment period in Table C1, including the average values, their mean differences, and the significance level of the t-test for these differences, denoted with stars. We find that during the pretreatment period, the endorsed doctors on average charge higher prices and provide more services.

Table C1: Pretreatment Comparison Between Treated and Control Doctors

	Treated Doctors		**Control Doctors**		
	Obs	Mean	Obs	Mean	Mean Diff
Paid Consultations:					
price	14,750	102.20	149,873	89.27	12.94***
quantity	14,750	9.06	149,873	3.84	5.22***
Free Consultations:					
quantity	5,304	9.41	70,482	1.77	7.63***

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

With the GSC method, we present summary statistics of key outcome variables of the endorsed group and the synthetic control group during the pretreatment period in Table C2, including the average values, their mean differences, and the significance level of the t-test for these differences, denoted with stars. We find that GSC method ensures the two groups are similar across the key outcome variables during the pretreatment period as none of the mean differences is statistically significant; i.e., with stars.

Table C2: Pretreatment Comparison Between Treated and Synthetic Control Doctors

	Treated Doctors		**SC Doctors**		
	Obs	Mean	Obs	Mean	Mean Diff
Paid Online Consultations:					
price	14,507	103.14	14,507	103.14	-0.00
quantity	14,507	9.19	14,507	9.19	-0.00
Free Online Consultations:					
quantity	5,304	9.41	5,304	9.41	0.00

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *None of the mean differences is statistically significantly different from zero. The number of observations is slightly lower than that in the raw data because the GSC method automatically drops doctors who have too few observations—less than eight in our case—in the pretreatment period.*

In addition to the mean difference comparison in Table C2, we further present the pretreatment trends of the outcome variables in Figure C1. The three rows show results for paid service price, paid service quantity, and free service quantity, respectively. The left three figures present the patterns between treated and control groups in the raw data while the right three figures present the patterns between treated and synthetic control groups with the GSC method. The close alignment between the two groups in the right panel demonstrates that the pretreatment parallel trends hold better with the GSC method, which has accounted for potential unobservables.

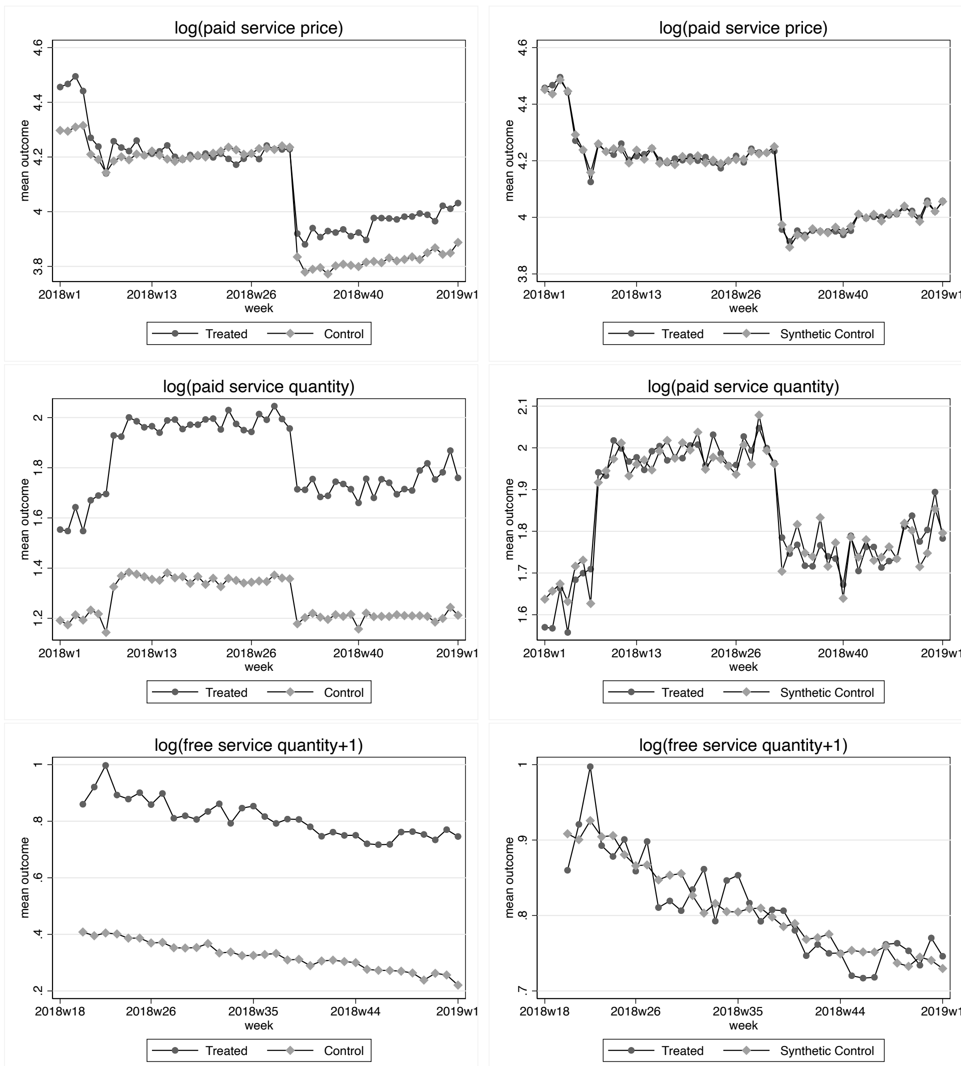


Figure C1: Comparison of Pretreatment Trends b/w Treated and (Synthetic) Control Groups

Notes: The four figures displayed in the top two rows represent the average price and quantity of paid services across three types (text/image package 1, text/image package 2, and phone call). Notably, text/image package 2 was introduced in week 32 in 2018. Given that both the price and quantity for this service are lower compared to the other two types, a sudden drop is observed in these figures.

D A Test on Potential Spillover on the Control Group

In our main analysis, we focus on the *newly* endorsed doctors, who serve as the treated group, and compare them with the never-endorsed doctors, who serve as the control group. To quantify the extent of any possible negative spillover effect due to endorsement on the control group, we conduct an additional analysis. In this analysis, we shift our attention to doctors who have endorsed multiple times and again in 2019 as the treated group, and compare them with the same control group of never-endorsed doctors.

Four potential scenarios regarding paid service price and quantity could happen, as summarized in Table D1. As a result of endorsement, multi-time endorsed doctors may or may not experience a positive quality signal, leading to a boost in both the price and quantity of their paid services. Conversely, the unendorsed doctors, i.e., the control group, may or may not face a decrease in demand due to potential negative spillover effects. Should both (Scenario 1) or either (Scenarios 2 & 3) the positive quality signal and the negative spillover be present, one would expect the estimated ATT between these two groups to be positive.

Table D1: Potential Outcomes Between Multi-Time Endorsed Doctors with Control Doctors

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Positive quality signal on multi-time endorsed doctors	Yes	Yes	No	No
Negative spillover on never-endorsed doctors	Yes	No	Yes	No
Estimated ATT between the two groups	Positive	Positive	Positive	Zero

However, our results, as shown in Table D2, reveal no significant differences post endorsement between the two groups, corresponding to Scenario 4. This suggests two things. First, the simple numerical increase on the endorsement badge does not seem to send a strong quality signal for multi-time endorsed doctors. Second, there is no notable negative spillover effect of endorsement on the control group. As a result, we conclude that the stable unit treatment value assumption is valid in our study. Note that this insignificant result is not driven by a lack of power, given that the number of multi-time endorsed doctors is greater than the number of newly endorsed doctors ($221 > 156$).

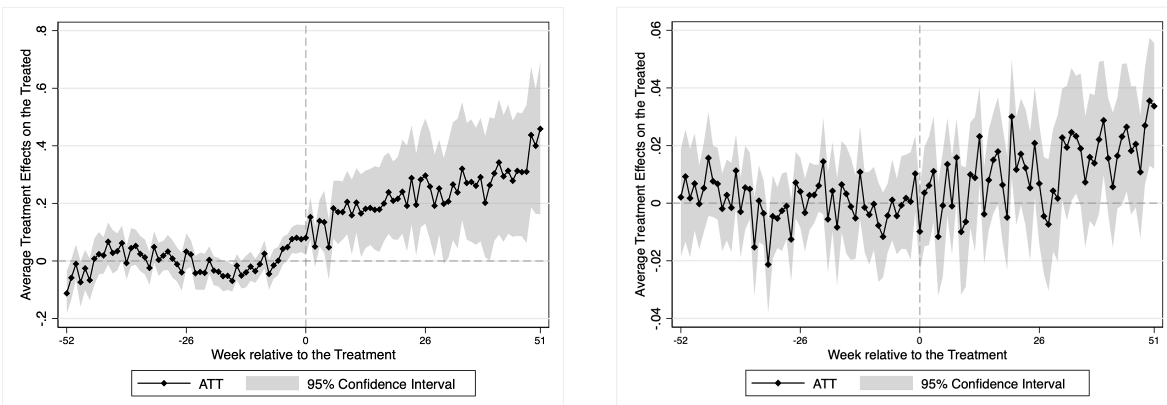
Table D2: Impact of Platform Endorsement on Multi-Time Endorsed Doctors

	(1) log(paid service price)	(2) log(paid service quantity)	(3) log(free service quantity)
ATT	0.0017	-0.0074	-0.054
	(0.041)	(0.036)	(0.069)

Notes: In Column (1) and Column (2), doctor-service fixed effects and week fixed effects are included. In Column (3), doctor fixed effects and week fixed effects are included. Standard errors are based on parametric bootstraps of 1,000 times. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

E Impact of Platform Endorsement on Number of Patient Requests and Doctor Acceptance Rates

For a paid online consultation to take place, a patient must first initiate a request and then this request needs to be accepted by the doctor. To get more direct evidence that platform endorsement leads to both an increase in demand by patients and an increase in supply by doctors, we separately estimate the impact on the number of patient requests and doctor acceptance rates. The results are reported in Figure E1. Figure E1a indicates that endorsed doctors receive more patient requests (ATT = 12.4% with std. err. = 8.6%) and Figure E1b indicates that endorsed doctors also accept a slightly higher proportion of patient requests during the posttreatment period (ATT = 1.2 pp with std. err. = 0.2 pp) . The findings indicate that the increase in service quantity is attributed to both an increase in the number of patient requests and an increase in doctor acceptance rates.



(a) log(# Requests) (b) Acceptance Rate

Figure E1: Impact on Requests and Acceptance Rates of Paid Online Services

Notes: These figures show the estimated ATT on log(# requests) and acceptance rate, along with 95% confidence intervals for each week before and after endorsement. We include doctor-service fixed effects and week fixed effects. The standard errors are based on parametric bootstraps of 1,000 times.

F Robustness Checks

Missing Values: Missing values in our data can be attributed to either a doctor's unavailability in a given week or a lack of patient requests. If it is the latter, then one could replace a missing value of price with the lagged value and replace a missing value of quantity with zero when studying the demand reaction. Given that our dataset includes three types of paid services (text/image package 1, text/image package 2, and phone call), we adopt the following approach when replacing missing values: if a request of any type is recorded for a doctor in a given week, we infer the doctor was available that week. Consequently, we can assign the lagged prices to missing values of prices and assign zero to missing values of quantity for that week, implying the doctor was available but did not receive any patient requests for those services. If no request of any type is recorded for a doctor in a given week, we still retain the missing values of price and quantity because doctors are more likely to be unavailable in that week.

Table F1 and Table F2 present the results on paid service price and quantity, respectively. In both tables, Column (1) mirrors the main results when we retain no observed activities as missing and Column (2) reports the new results when we replace missing values following the above approach. The results are consistent between the two.

Table F1: Robustness Check on Missing Value of Price

	log(paid service price)	
	(1) retain missing values	(2) replace missing values with lagged value
ATT	0.087**	0.071**
	(0.044)	(0.022)

Notes: Doctor-service fixed effects and week fixed effects are included. Standard errors are based on parametric bootstraps of 1,000 times. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table F2: Robustness Check on Missing Value of Quantity

	log(paid service quantity)	
	(1) retain missing values	(2) replace missing values with zero
ATT	0.197***	0.182**
	(0.073)	(0.077)

Notes: Column (1) shows the estimated ATT on $log(paid\ service\ quantity)$ while Column (2) shows the estimated ATT on $log(paid\ service\ quantity + 1)$ due to the replacement of missing values with zero. Doctor-service fixed effects and week fixed effects are included in both columns. Standard errors are based on parametric bootstraps of 1,000 times. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Difference-in-Differences (DiD): To check the robustness of our main findings, we use the standard DiD method as the first alternative approach. The advantage of this method is its simplicity in being free from any weighting or matching process. However, the main drawback of this approach is that the parallel trend assumption may not hold if there exist time-varying unobserved factors that differ between endorsed and unendorsed doctors. Despite this limitation, we present the results from the DiD method in Table F3. We find that while the estimated effects are smaller compared to those obtained using the GSC approach, our key findings remain consistent.

Table F3: DiD Results

	(1) log(paid service price)	(2) log(paid service quantity)	(3) log(free service quantity)
ATT	0.077***	0.028***	-0.114***
	(0.0035)	(0.0097)	(0.010)

Notes: In Column (1) and Column (2), doctor-service fixed effects and week fixed effects are included. In Column (3), doctor fixed effects and week fixed effects are included. Robust standard errors are reported. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Propensity Score Matching with Difference-in-Differences (PSM-DiD): We use the PSM-DiD method as the second alternative approach to the GSC method. The PSM-DiD method relies on the uncounfoundedness assumption, where no observed factors are correlated with the treatment, conditional on the observed variables. Assuming that the unconfoundedness assumption holds, we conduct matching based on the variables that the platform used in the endorsement selection process, including service quantity, patient reviews and waiting time. The results are detailed in Table F4, where we observe consistent outcomes with the main results.

Table F4: PSM-DiD Results

	(1) log(paid service price)	(2) log(paid service quantity)	(3) log(free service quantity)
ATT	0.081***	0.135***	-0.081***
	(0.0052)	(0.014)	(0.005)

Notes: In Column (1) and Column (2), doctor-service fixed effects and week fixed effects are included. In Column (3), doctor fixed effects and week fixed effects are included. Robust standard errors are reported. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Alternative Functional Form: Instead of using logarithmic transformation, we present the results with absolute measures of price and quantity using GSC method in Table F5. The results are consistent.

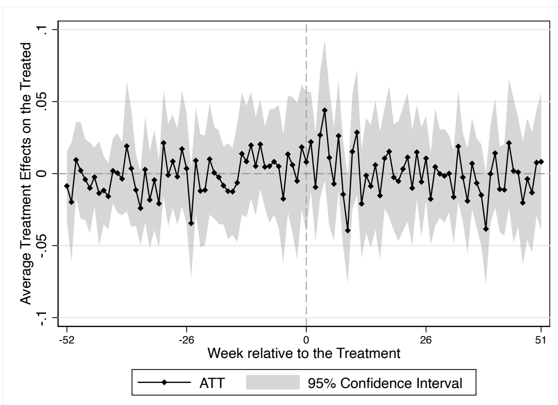
Table F5: Alternative Functional Form with Absolute Measures

	(1) paid service price	(2) paid service quantity	(3) free service quantity
ATT	10.27***	5.84***	-4.89***
	(3.60)	(0.91)	(1.26)

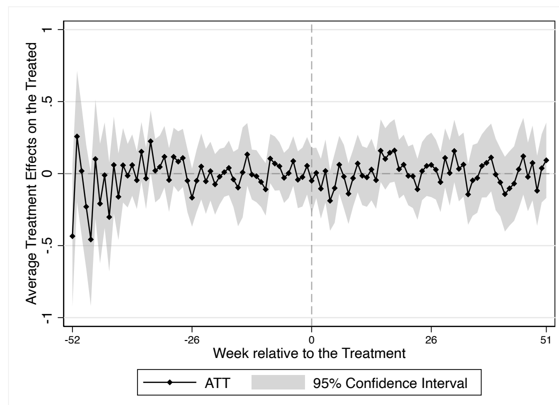
Notes: In Column (1) and Column (2), doctor-service fixed effects and week fixed effects are included. In Column (3), doctor fixed effects and week fixed effects are included. Standard errors are based on parametric bootstraps of 1,000 times. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

G Analysis on Other Quality Measures

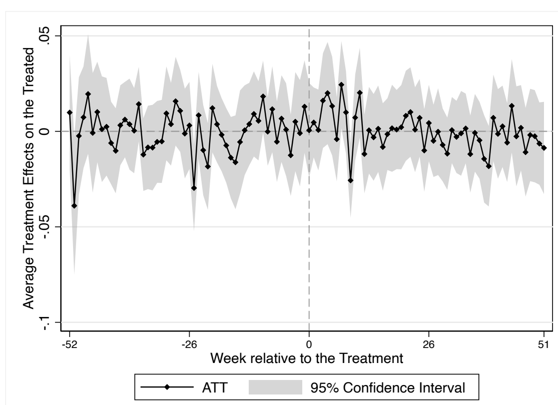
Patient Reviews: We present the results of the impact of platform endorsement on patient reviews as a measure for service quality. Specifically, we focus on three metrics: the ratio of positive ratings in reviews, the average word count of reviews, and the average sentiment score of reviews at the doctor-week level. We report the results for only paid services because the number of observations for free services is too few to generate reliable estimates with the GSC method. Across the ratio of positive ratings in reviews (ATT = 0.000, p-value = 0.913), word count in a review (ATT = 0.007, p-value = 0.763), and sentiment score of reviews (ATT = 0.000, p-value = 0.966), we do not find any statistically significant effects as a result of platform endorsement.



(a) % Positive Ratings in Reviews



(b) log(Word Count in a Review)



(c) Review Sentiment

Figure G1: Impact on Patient Reviews of Paid Services

Notes: These figures show the estimated ATT on the three metrics of patient reviews on paid services and 95% confidence intervals for each week before and after endorsement. We include both doctor fixed effects and week fixed effects. The standard errors are based on parametric bootstraps of 1,000 times.

Phone Call Consultation Duration: We present the results of the impact of platform endorsement on phone call consultation duration as a measure for service quality. We find no statistically significant change on phone call duration as a result of endorsement (ATT = -0.012, p-value = 0.844).

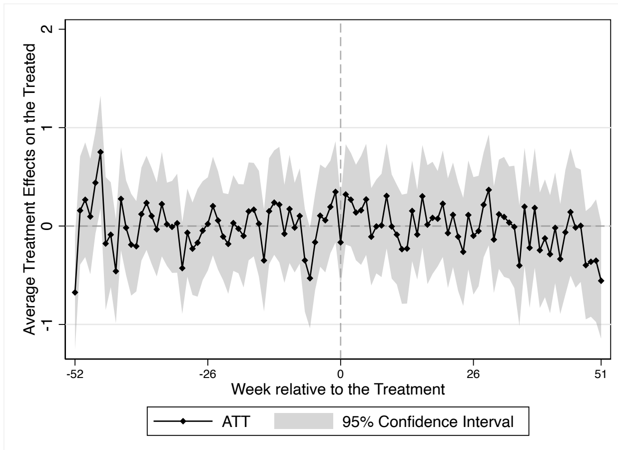


Figure G2: Impact on Phone Call Consultation Duration

Notes: This figure shows the estimated ATT on phone call duration and 95% confidence intervals for each week before and after endorsement. We include doctor fixed effects and week fixed effects. The standard errors are based on parametric bootstraps of 1,000 times.

Waiting Time: We present the results of the impact of platform endorsement on waiting time as a measure for service quality. We report results on phone call consultations in Figure G3. The results (ATT = -0.003, p-value = 0.930) indicate that endorsement has no significant impact on waiting time for phone call consultations. Waiting time data are less relevant and not available for text/image consultations because this type of consultation starts immediately after the doctor accepts the patient's request. If the request is not picked up in time, it is canceled and refunded automatically.

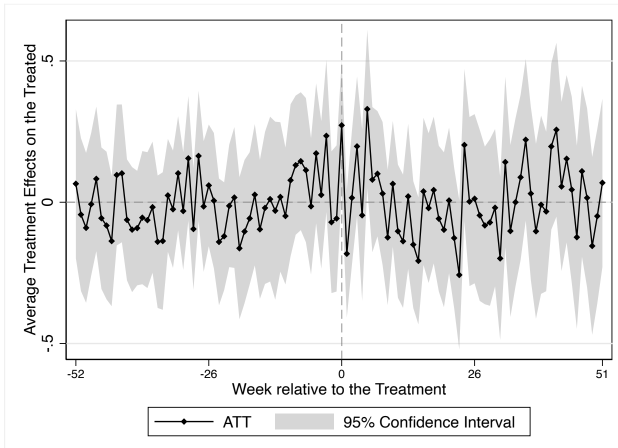


Figure G3: Impact on Waiting Time

Notes: These figures show the estimated ATT on log(waiting time) for phone call consultations and 95% confidence intervals for each week before and after endorsement. We include both doctor fixed effects and week fixed effects. The standard errors are based on parametric bootstraps of 1,000 times.

H More Information on Pro-Social and Non Pro-Social Doctors

Table H1: Summary Statistics of Pro-Social and Non-Pro-Social Doctors

	Pro-Social Doctors		**Non-Pro-Social Doctors**		
	Obs	Mean	Obs	Mean	Mean Diff
Free service quantity	78	945.65	78	46.68	898.97***
Paid online service price	78	77.84	74	121.37	-43.52***
Paid service quantity	78	654.12	78	774.46	-120.35
Gender (male=1)	78	0.78	78	0.72	0.06
Age	78	43.97	78	43.46	0.51
Phd Degree	78	0.44	78	0.49	-0.05
Megacity	78	0.56	78	0.65	-0.09
Chief Doctor	78	0.31	78	0.36	-0.05
High Severity Department	78	0.21	78	0.22	-0.01
Tenure on the Platform (years)	78	5.40	78	5.96	-0.56

Notes: Megacity includes Beijing, Shanghai, and Guangzhou. High severity department includes Organ Transplantation, Cardiovascular Medicine, Cardiovascular Surgery, Neurology, Neurosurgery, Oncology, and Thoracic Surgery. Across all the observed doctor attributes, none of the differences is statistically significant between the two groups.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We examine how doctors with different pro-social levels vary in their reactions towards endorsement. To conduct this analysis, we regress the estimated doctor-week level ATTs of each of the following outcomes, including paid service price, paid service quantity, and free service quantity, on doctors' pro-social levels. The results in Table H2 indicate that doctors with higher pro-social levels tend to make smaller increases in paid service prices, provide more paid services, and decrease their provision of free services more.

Table H2: Relationship Between Pro-Social Level and the Estimated ATTs

	Estimated ATTs on		
	log(Paid Service Price)	log(Paid Service Quantity)	log(Free Service Quantity)
Pro-Social Level	-0.140***	0.124*	-1.486***
	(0.035)	(0.071)	(0.069)
Week FE	Yes	Yes	Yes
No. of Obs.	16,402	16,644	7,904
R-squared	0.0029	0.0032	0.0637

Notes: We cannot include doctor fixed effects because pro-social level is a doctor-level time invariant attribute. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$