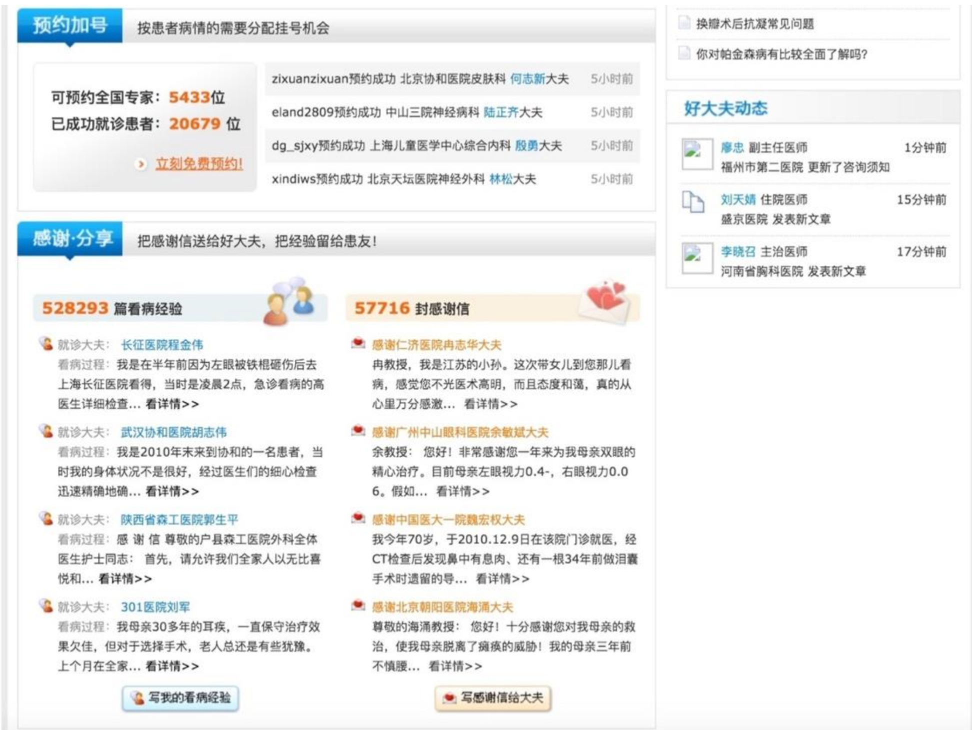
Online Appendix for “Informal Payments and Doctor Engagement in Online Health Community: An Empirical Investigation Using Generalized Synthetic Control”

Online Appendix A: The Sample Pages of the OHC

Figure A.1. A Sample Consultation Page

Before:



After:

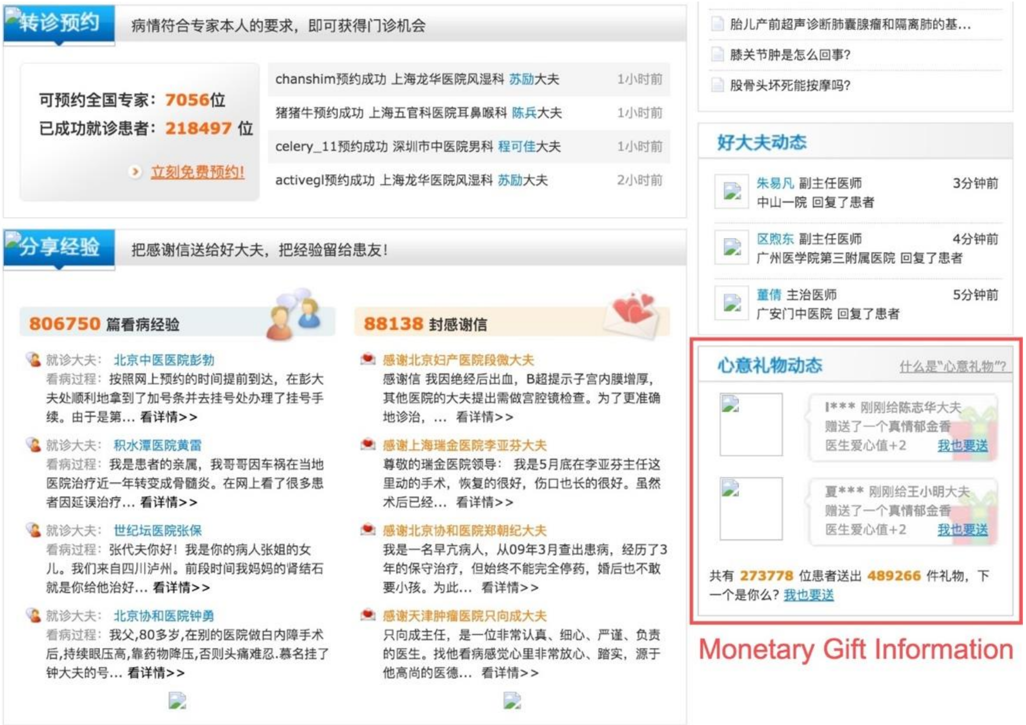


Figure A.2 The Design of the Home Page Before and After the Monetary Gift Feature Launches

Note that although only 5% of patients in our dataset have ever sent a monetary gift, approximately 77% of the doctors have received a monetary gift in our sample period.

Online Appendix B: The Keywords of LDA-Derived Topics and Text Mining Results

In our study, we use the LDA model to capture latent topics in medical consultation questions. Then we control for the extracted 30 topic variables in our regression models. It is worth noting that the coefficients on the topic variables are all insignificant, which indicates that differences in medical topics do not have a significant impact on the number of responses and response length. A possible explanation is that a doctor's responses depend largely on the content of patients' consultations instead of medical topics. In other words, the doctor responds mainly to specific questions that the patient asks. Thus, the number and length of responses do not vary significantly with the topics. The keywords for each topic are presented in Table B.1.

Table B.1. Highest-Probability Keywords for Each Topic

Topic #	Keywords	Label
1	近视(Myopia), 散光(Astigmatism), 晶体(Crystal), 矫正(Correction), 早衰(Premature Aging), 单抗(Monoclonal Antibodies), 雷珠(Ranibizumab), 致密(Dense)	Myopia
2	先心病(Congenital Heart Disease), 缺损(Defect), 室内隔(Ventricular Septum), 心外科(Cardiac Surgery), 分流(Shunt), 畸形(Deformity), 开胸(Thoracotomy), 杂音(Murmur)	Heart Disease
3	艾滋病(AIDS), 疫苗(Vaccine), 艾滋(AIDS), 感染(Infection), 肾虚(Kidney Deficiency), HIV(HIV), 高危(High Risk), 恐艾(Phobia), 手淫(Masturbation)	AIDS
4	破伤风(Tetanus), 摔倒(Fall), 咬伤(Bite), 肉毒素(Botox), 伤口(Wound), 淋巴瘤(Lymphoma), 瘘(Fistula), 流血(Bleeding)	Surgical Disease
5	狂犬(Rabies), 破损(Damaged), 发烧(Fever), 阴天(Cloudy Day), 下雨(Rain), 呼吸(Breathe), 疫苗(Vaccine), 声音(Sound)	Rabies
6	瘙痒(Itching), 腹(Belly), 阴唇(Labia), 特纳氏(Turner), 水银(Mercury), 股骨(Femur), 洗液(Lotion), 内裤(Underpants)	Gynecology
7	减肥药(Weight Loss Pills), 头晕(Dizziness), 胆囊结石(Gallstone), 减肥(Lose Weight), 虚弱(Weak), 宫寒(Cold Uterus), 吃饭(Eat)	Weight Control
8	结膜炎(Conjunctivitis), 健康(Health), 目力(Eyesight), 寻找(Search), 三叉神经痛(Trigeminal Neuralgia), 肿胀(Swelling), 流泪(Weep)	Conjunctivitis & Trigeminal Neuralgia
9	红疹(Rash), 拉贝(Labello), 肾丸(Kidney Pills), 艾滋病毒(HIV),肾病(Nephropathy), 喉结(Throat Knot), 水肿(Oedema), 血尿(Hematuria)	Kidney Disease
10	肠粘连(Intestinal Adhesions), 便秘(Constipation), 烫伤(Scald), 腰困(Lumbago), 大肠(Large Intestine), 小孔(Pinhole), 胃痛(Stomachache), 腹泻(Diarrhea)	Enteropathy
11	脑鸣(Tinnitus), 前置(Preposition), 板蓝根(Radix Isatidis), 冰糖(Crystal Sugar), 风寒(Cold), 饮用(Drink), 雪梨(Pyrus Nivalis), 鼻涕(Snot)	Cold & Flu
12	转流(Bypass), 心内膜炎(Endocarditis), 膜炎(Meningitis), 膀胱炎(Cystitis), 肩胛骨(Shoulder Blade), 酸麻(Numb), 皮炎(Dermatitis), 痒(Pruritus)	Inflammation
13	下腹部(Lower Abdomen), 绿色(Green), 食指(Index Finger), 他巴唑(Tabazole), 甲亢(Hyperthyroidism), 甲状腺(Thyroid), 激素(Hormone), 口渴(Thirsty)	Hyperthyroidism
14	甲状腺(Thyroid), 手术(Surgery), 照片(Photo), 填写(Fill in), 肿瘤(Tumor), 肥大(Hypertrophy), 结节(Nodular), 休息(rest)	Thyroid Disease
15	妊高症(Pregnancy Induced Hypertension), 大动脉炎(Arteritis), 卡维地洛片(Carvedilol), 雷诺(Raynaud Disease), 赘肉(Excess Fat), 小球(Glomerulus), 系膜区(Mesangial Region), 血压(Blood Pressure)	Hypertension
16	下垂(Sagging), 尖锐湿疣(Condyloma Acuminatum), 凸起(Bulge), 红点(Red Dot), HPV(HPV), 性行为(Sex), 肛门(Anus), 传播(Spread)	Condyloma Acuminatum
17	运动神经元(Motor Neuron), 胃窦(Antrum of Stomach), 胃底	Stomach

	(Fundus of stomach), 贲门(Cardia), 粘膜(Mucosa), 下压(Press Down), 胃体(Gastric Body), 上压(Press Up), 食管(Esophagus)	
18	全麻(General Anesthesia), 冷冻(Freezing), 疣(Wart), 肢端肥大(Acromegaly), 敷贴(Dressing),肥大症(Acromegaly), 生长激素(Growth Hormone)	Frostbite & Acromegaly
19	粉刺(Acne), 毛囊炎(Folliculitis), 坑(Pit), 积血(Hematocele), 白头(Whitehead), 油光(Glossy), 挤压(Extrusion)	Face Problem
20	多囊肾(Polycystic Kidney), 裂孔(Crack), 手心(Palm), 肾盂肾炎(Pyelonephritis), 尿痛(Dysuria), 肿物(Tumor), 肾炎(nephritis)	Nephropathy
21	黄褐斑(Chloasma), 可降解(Biodegradable), 烧伤(Burn), 脓包(Pustule), 痣(Nevus), 雀斑(Freckles), 色斑(Dark Spots)	Pigmentation
22	疤痕(Scar), 电疗(Electrotherapy), 类固醇(Steroid), 磨疤(Flatten Scar), 压衣法(Pressure Garment), 胶原(Collagen), 烫伤(Scald)	Scar
23	转诊(Referral), 预约(Appointment), 挂号(Register), 指定(Assign), 隐私(Privacy), 看病(See a Doctor), 医院(Hospital)	Medical Consultation
24	胃胀(Abdominal Distension), 嗳气(Belch), 下腹(Lower Abdomen), 痤疮(Acne), 倦怠(Burnout), 胃疼(Stomachache), 消化(Digestion), 进食(Take Food)	Indigestion
25	疗养(Recuperation), 淀粉样变(Amyloidosis), 多汗症(Hyperhidrosis), 醇片(Stanozolol Tablets), 激素(Hormone), 内衣(Underwear), 紊乱(Disorder), 治疗(Treatment)	Endocrine System
26	堵闷(Blocking), 肿起(Swelling), 霉菌性(Mycotic), 泌乳素瘤(Prolactinoma), 宫颈(Cervix), 糜烂(Erosion), 阴道炎(Vaginitis), 分泌(secrete)	Gynecological Inflammation
27	内膜(Intima), 紫癜(Purpura), 过敏性(Anaphylaxis), 腺瘤(Adenoma), 干净(Clean), 免疫系统(Immune System), 鼻炎(Rhinitis), 哮喘(Asthma)	Allergy
28	靶向(Targeted), 腺癌(Adenocarcinoma), TCT(TCT), 肿瘤(Tumor), 结肠癌(Colon Cancer), 癌细胞(Cancer Cell), 晚期(Advanced Stage), 筛查(Screening)	Cancer
29	中耳炎(Tympanitis), 脂溢(Seborrhea), 畏寒(Chills), 耳鸣(Tinnitus), 流脓(Pus), 失聪(Deaf), 残疾(Disability), 疼痛(Pain)	Ear Problem
30	拔牙(Tooth Extraction), 易激(Irritable), 伽马刀(Gamma Knife), 鱼刺(Fishbone), 牙龈炎(Gingivitis), 口臭(Halitosis), 洗牙(Teeth Cleaning), 拍片(Photography)	Dental & Oral

Online Appendix C: Correlations of Variables

Table C.1. Correlations of Variables: Panel Data

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) AveResNum	1.0000						
(2) AveConsNum	0.4892	1.0000					
(3) AveResLen	0.6584	0.3091	1.0000				
(4) AveConsLen	0.4048	0.2687	0.5832	1.0000			
(5) AveInterval	-0.0445	0.0225	-0.0001	0.0041	1.0000		

(6) ThreadCount	0.0637	-0.0358	-0.0130	-0.0222	-0.2652	1.0000	
(7) AveQuesLen	0.1030	0.0963	0.1084	0.6969	-0.0010	-0.0149	1.0000

Table C.2. Correlations of Variables: Consultation-Level Data

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) ResNum	1.0000												
(2) ConsNum	0.8712	1.0000											
(3) ResLen	0.7124	0.6335	1.0000										
(4) ConsLen	0.6407	0.7162	0.5543	1.0000									
(5) GiftOnly	0.1714	0.1641	0.1362	0.2064	1.0000								
(6) LetterOnly	0.0574	0.0596	0.0456	0.0725	-0.0224	1.0000							
(7) Gift&Letter	0.1377	0.1360	0.0993	0.1472	-0.0165	-0.0070	1.0000						
(8) ClinicDay	-0.0093	-0.0137	-0.0072	-0.0213	-0.0116	-0.0067	-0.0086	1.0000					
(9) Weekend	0.0059	0.0056	0.0085	0.0035	0.0007	0.0045	0.0060	-0.3512	1.0000				
(10) DiagFee	0.0587	0.0947	0.0601	0.1682	0.0635	0.0327	0.0345	-0.0294	0.0028	1.0000			
(11) Tenure	-0.0889	-0.0432	-0.0608	0.0478	0.0480	0.0181	0.0089	0.0038	-0.0023	0.1262	1.0000		
(12) ClinicTitle [High]	-0.0273	-0.0063	-0.0327	0.0595	0.0307	0.0171	0.0109	-0.0192	0.0024	0.1351	0.3476	1.0000	
(13) ClinicTitle [Low]	-0.0001	-0.0043	0.0351	-0.0318	-0.0199	-0.0085	-0.0065	-0.0093	0.0076	-0.0656	-0.1706	-0.1535	1.0000

Online Appendix D: Comparison of Related Work and Our Study

There are some recent studies (Jing et al. 2019; Peng et al. 2020; Wang et al. 2020) that examine the effect of monetary incentives on OHCs. The differences between our research and these studies are listed in the following table. We want to point out that the most significant difference is that our main results indicate a crowding-out effect of additional monetary rewards, which is different from those of these prior studies.

Table D.1. Comparison of Related Work and Our Study

Study	OHC Features	Time Periods	Dependent Variables	Main Independent Variables	Moderating Variables	Data Granularity
Jing et al. (2019)	Paid consultation	Pre-launch & post-launch	Number of free services	Monetary incentives	Consultation fee and doctor rating	Doctor-month panel data
Wang et al. (2020)	Monetary gifting	Post-launch	The average word count	Monetary value	Number of gifts and service price	Consultation thread-level

Peng et al. (2020)	Monetary gifting	Post-launch	The ratio of the word count of the doctor to that of the patient	Monetary gifts	Affective and instrumental elements and tie strength	Consultation thread-level
Our Study	Monetary gifting	Pre-launch & post-launch	The average number of responses and the average total response length	Launch of the feature & monetary gifts	Monetary and nonmonetary options, social status, and carryover effect	Doctor-week panel data & Consultation thread-level

(a) We illustrate the main differences between our study and Jing et al. (2019) as follows. First, our research question is different from theirs. We examine the feature of monetary gifting, while Jing et al. (2019) investigate the feature of paid consultation. Different from paid consultation, monetary gifting is a kind of voluntary payment from patients. The monetary gifts are neither very expensive nor serve as serious financial payments. Thus, the conclusions of our study cannot be inferred from their results. Second, the dependent variables we use are different. Jing et al. (2019) take the number of free services a doctor provides as the dependent variable to measure doctors' prosocial behavior. We measure the level of doctor engagement using the average number of responses and the average total response length. Because a patient directly benefits from doctors' online responses, we believe that our measures can better evaluate doctors' prosocial behaviors from the perspective of patients. Third, moderating variables we examine in Section 4.4 are different from those of Jing et al. (2019). We investigate the heterogeneous effect of digital gifting from the perspective of monetary and nonmonetary options, social status, and carryover effect, while Jing et al. (2019) examine the moderating effects of the consultation fee and the doctor rating.

In addition, we want to point out that our results are different from those of Jing et al. (2019) because our study focuses on doctors' voluntary services instead of paid services. In terms of paid services (with a business mindset), prior literature has widely explored the relationship between price and quantity/quality and generally found a monotonically positive relationship between them (Curry and Riesz 1988; Gorn et al. 1991). In other words, mandatory payments in a business context can increase quantity/quality. However, with regard to voluntary services, the relationship may not always hold. Prior studies have found that intrinsic motivations can be crowded out by extrinsic incentives (e.g., monetary incentives) for prosocial behaviors (Bénabou and Tirole 2006). For example, Titmuss (1970) finds that paying blood donors may actually reduce the supply. Bellé (2015) empirically examines the effects of monetary rewards in the public healthcare sector and shows that monetary incentives for prosocial activities can crowd out the image motivation of public healthcare employees. The experimental results of Exley (2008) also indicate that image concern is an important factor that affects volunteering activities. Our findings are consistent with these prior studies. Specifically, our results show that extra monetary reward has a crowding-out effect on doctors' voluntary engagement and contributes to the literature on prosocial behavior in the context of the online health community.

(b) Our study mainly differs from Wang et al. (2020) in the following aspects. First, the research periods are different. We examine the impact of the introduction of the gifting feature using data in both pre-launch and post-launch periods, while Wang et al. (2020) only use data in the post-launch period to investigate the monetary value of gifts. Second, the dependent variables we use are different from that of Wang et al. (2020). We use both the average number of responses and the average total response length, while Wang et al. (2020) only use the average word count to measure the quality of doctors' online consultation services. Third, moderating variables we examine are different from those of Wang et al. (2020). We consider monetary and nonmonetary options, social status, and carryover effect, while Wang et al. (2020) investigate the number of gifts and service prices. Fourth, we have done more investigation into the impact of informal payments, especially from the perspective of the introduction of the new gifting feature.

(c) The followings are the main differences between our study and Peng et al. (2020). First, the research periods are different. We examine the impact of the introduction of the gifting feature using data in both pre-launch and post-launch periods, while Peng et al. (2020) only use data in the post-launch period to investigate monetary gifts. Second, the dependent variables we use are different. Peng et al. (2020) use the ratio of the word count of the doctor to that of the patient as the dependent variable to measure service quality. However, we measure the level of doctor engagement using the average number of responses and the average total response length. Third, moderating variables we investigate in Section 4.4 are different from those of Peng et al. (2020). We investigate the heterogeneous effect of digital gifting from the perspective of monetary and nonmonetary options, social status, and carryover effect, while Peng et al. (2020) examine the moderating roles of affective and instrumental elements and tie strength between physicians and patients. Besides, our findings are not contradictory to the results of Peng et al. (2020). In Section 4.4, we examine the effect of digital gifting after the new feature launches using consultation thread-level data in the posttreatment period. Our results show that doctors deliver responses more actively if they have been given digital gifts in a consultation, which is similar to the main findings of Peng et al. (2020). To sum up, our study is different from Peng et al. (2020), and our findings are not contradictory to the results of Peng et al. (2020). We have done more investigation into the impact of informal payments, especially from the perspective of the introduction of the new gifting feature.

Online Appendix E: Survival Analysis of Doctor Engagement

We define a doctor as inactive (an "event") if he or she does not respond to any consultation for six months in the OHC (the results are similar when using a time period of three months or nine months). Specifically, we use $Inactive_{it}$ to represent whether doctor *i* has become inactive at time *t* (1 represents inactive and 0 represents active).

First, we estimate the survival function for active doctors using the Kaplan–Meier method (Kaplan and Meier 1958). We then plot the estimated survival function in Figure E.1. We can see that after the launch of the new gifting feature, the survival probability drops more rapidly than before, indicating that the introduction of extra monetary incentives may induce more doctors to quit the OHC platform (to become inactive).

Second, we use a parametric survival model, the Weibull hazard model, to quantitatively evaluate the impact of the launch of the new gifting feature on time to the occurrence of becoming inactive. Specifically, the hazard rate of becoming inactive estimated by the Weibull hazard model is specified as:

$$h_i(t|PostLaunch_{it}) = pt^{p-1}e^{\beta_0+\beta_1 PostLaunch_{it}} \quad , \tag{E.1}$$

where p is the ancillary shape value parameter that describes the hazard rate without explanatory variables. $PostLaunch_{it}$ represents our independent variable of interest. The estimated coefficient of

$PostLaunch_{it}$ is 0.511 ($\widehat{\beta_1} = 0.511$, $se = 0.027$). Our results indicate that the launch of the new gifting feature significantly increased the risk of a doctor becoming inactive in the OHC. In general, the introduction of the new gifting feature increases the probability of a doctor becoming inactive in the OHC by 67% ($e^{\widehat{\beta_1}} = 1.67$), with everything else being equal.

The survival analysis results show that there exists a declining number of active doctors on the OHC platform, which provides further support for the crowding-out effect of additional monetary rewards on doctor engagement.

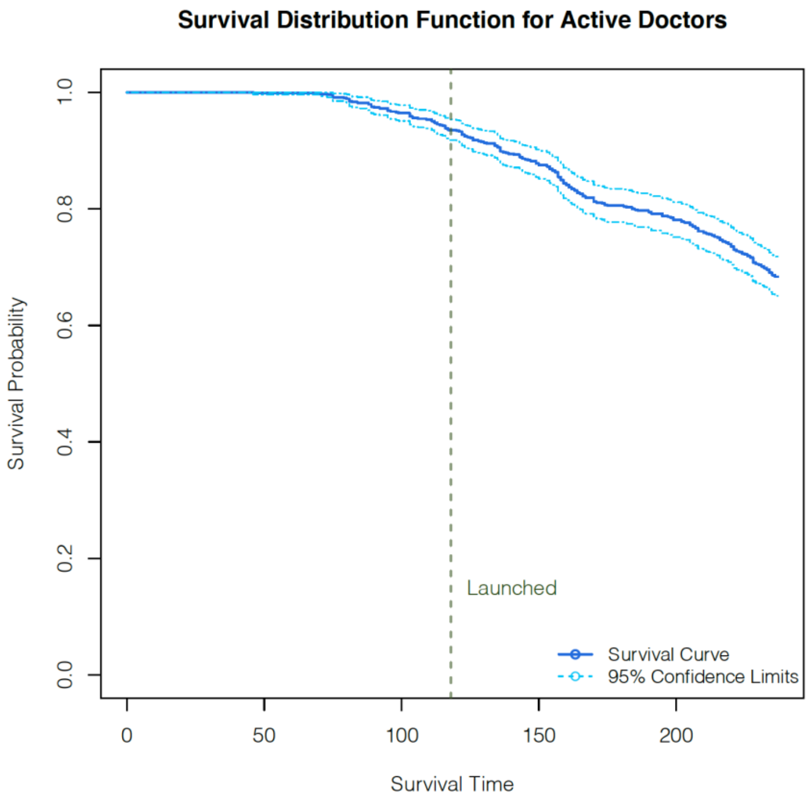


Figure E.1. Survival Distribution Function for Active Doctors

Online Appendix F: Interrupted Time Series Analysis Regression with Fixed Effects

We combine interrupted time series analysis regression with fixed effects to improve the robustness of our empirical analysis. Following Bernal et al. (2017), we estimate the following segmented regression model with fixed effects:

$$AveResNum_{it} = d_i + \beta_0 + \beta_1 T + \beta_2 PostLaunch_t + \beta_3 (T \times PostLaunch_t) + \beta_4 Controls + \varepsilon_{it}\,, \quad (\mathrm{F.1})$$

$$\log(AveResLen_{it}) = d_i + \beta_0 + \beta_1 T + \beta_2 PostLaunch_t + \beta_3 (T \times PostLaunch_t)$$
$$+\beta_4 Controls + \varepsilon_{it}\,, \tag{F.2}$$

where T is the time period unit index in our sample, which is 1, 2, 3, …, β_1 represents the change in dependent variables associated with a time unit increase, β_2 indicates the immediate effect following the introduction of the monetary gift feature, and β_3 is the slope change following the introduction of the new feature. The estimation results of Equations (F.1) and (F.2) are shown in Table F.1. We can see that the coefficients on $PostLaunch_t$ are significantly negative, which are consistent with our main results.

Table F.1. Robustness Checks: Addressing Endogeneity Concerns

Variables	(1) AveResNum, ITS	(2) log(AveResLen), ITS
T	-0.014*** (0.002)	-0.012*** (0.001)
PostLaunch	-1.343*** (0.163)	-0.969*** (0.108)
T × PostLaunch	0.014*** (0.002)	0.010*** (0.001)
AveInterval	-0.003*** (0.001)	-0.006*** (0.001)
ThreadCount	0.010*** (0.002)	0.008*** (0.002)
AveQuesLen	0.000*** (0.000)	-0.000*** (0.000)
AveConsNum	0.448*** (0.021)	
log(AveConsLen)		0.480*** (0.018)

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are in parentheses.

Online Appendix G: Short-Term and Long-Term Treatment Effects

We add a new moderating variable, $LongTerm_t$, into our regression specifications to examine the long-term effect and re-estimate the models. The variable, $LongTerm_t$, is a dummy variable that equals 1 for the latter half of the posttreatment period and 0 otherwise. Thus, the short-term treatment effect is given by β_2 while the long-term treatment effect is captured by $\beta_2 + \beta_3$. The estimation results are presented in Table G.1. We can see that the coefficients on the two interaction variables, β_2 and β_3, are both significantly positive, indicating that the treatment effect remains significant over time. The results also reveal that the long-term treatment effect is greater than the short-term treatment effect because $\beta_2 + \beta_3$ is larger than β_2.

$$\begin{aligned} AveResNum_{it} &= d_i + \beta_0 + \beta_1 PostLaunch_t + \beta_2 (PostLaunch_t \times ReceiveGift_{it}) \\ &+ \beta_3 (PostLaunch_t \times ReceiveGift_{it} \times \boldsymbol{LongTerm_t}) + \beta_4 Controls \\ &+ \varepsilon_{it}\,, \end{aligned} \tag{G.1}$$

$$\begin{aligned} &\log(AveResLen_{it}) \\ &= d_i + \beta_0 + \beta_1 PostLaunch_t + \beta_2 (PostLaunch_t \times ReceiveGift_{it}) \\ &+ \beta_3 (PostLaunch_t \times ReceiveGift_{it} \times \boldsymbol{LongTerm_t}) + \beta_4 Controls \\ &+ \varepsilon_{it}\,, \end{aligned} \tag{G.2}$$

Table G.1. Robustness Checks: Examining Long-term Effects

Variables	(1) AveResNum, CRT	(2) log(AveResLen), CRT
PostLaunch	-0.237*** (0.037)	-0.404*** (0.031)
PostLaunch ×ReceiveGift	0.064*** (0.021)	0.034*** (0.011)
PostLaunch ×ReceiveGift ×LongTerm	0.080*** (0.022)	0.031*** (0.010)
AveInterval	-0.002* (0.001)	-0.005*** (0.001)
ThreadCount	0.006*** (0.002)	0.005*** (0.002)
AveQuesLen	0.000** (0.000)	-0.000*** (0.000)
AveConsNum	0.452*** (0.022)	
log(AveConsLen)		0.490*** (0.020)

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are in parentheses.

Online Appendix H: Post-Analysis Interview

Our empirical analyses indicate a significantly negative relationship between the introduction of the monetary gift feature and doctor engagement in the OHC. Although the crowding-out hypothesis is supported by the empirical results and additional analyses, they cannot provide direct evidence of a crowding-out effect at play. To address this issue, we conducted a series of semi-structured interviews with doctors who had registered before the launch of the feature and provided free responses to patients' consultations (Eisenhardt and Graebner 2007; Kwon et al. 2022; Salge et al. 2022). Specifically, we randomly reached out to 24 of these doctors, and 10 doctors among them agreed to participate in the interviews. These doctors are from different specialties, including cardiology, ophthalmology, neurology, and general surgery, and thus are highly representative of the doctors in the OHC. The interviews include several open-ended questions about why they participated in the OHC and their perceptions of whether the introduction of monetary gifts affects their motivation to contribute.

In terms of the motivation to participate in the OHC, all the interviewees stated that they initially used the platform because they wanted to help the patients. A few illustrative responses are listed below:

> *"I believe in the principle of "give more, expect less." At that time, the consultation service of the platform was totally free, and not many doctors were willing to spend time to do this. But I thought it was convenient to use this platform to communicate with patients online and it was very helpful to them, so I joined."*
>
> *"Well, the principle of a doctor is to treat patients and save them, and through this platform I can help more patients. I have already replaced my original hobby by answering questions for patients, and I don't consider it as my job when I do it, but a hobby, so it's not a burden, it's something I will do naturally, and the joy I get from it is also a lot."*
>
> *"I hope to help more people. In my spare time, I am happy if I can help patients."*

In connection to how the introduction of extra monetary rewards affects doctor engagement, we argue that, in the context of voluntary services, monetary payments may crowd out doctors' intrinsic motivations and lead to a lower level of engagement. The crowding-out effect underlying the negative effect of introducing extra monetary rewards is corroborated by the interviewees. Two doctors said they were indifferent to monetary gifts, and the remaining eight were not in favor of launching monetary gifts:

> *"I was not in favor of the inclusion of monetary gifts at that time. We came here to voluntarily help patients, not because we wanted to make money. We will answer patients' questions without the gift, but the introduction of monetary gifts is a bit against our original intention."*
>
> *"The introduction of monetary gifts somewhat monetizes love and appreciation, and I would*

rather patients send me free thank-you letters."

"I personally feel that monetary gifts are not necessary. For me, the best way to thank me is to follow medical advice well and maintain a healthy body. I don't like that little monetary reward. Monetary gifts are really not necessary."

One doctor even mentioned that he wrote on the bulletin board (on the personal page in the OHC) to ask patients not to send monetary gifts:

"I came to this platform with no expectation of profit in return. I didn't like the idea of monetary gifts. After the launch of the monetary gifts, I wrote on the bulletin board to tell patients not to send these monetary gifts. I also told them that if they really wanted to express the gratitude, they can give a thank-you letter or write a review, which costs nothing and provides a reference for other patients."

Taken in sum, the qualitative evidence from doctors in the OHC helps us ground the work in reality and provide additional support for our main findings.

Online Appendix I: Identity Theory and Our Implications to the Theory

In our study, we find that although the introduction of monetary gifts has a crowding-out effect in general, doctors who actually receive the gifts will respond more actively to consultation questions. We try to use the identity theory as a theoretical lens to explain the underlying mechanism. As denoted by Stets and Burke (2000), the most significant difference between identity theory and social identity theory is that the former is based on a role perspective (what one does) while the latter is based on a group perspective (what one is). In our context, we focus on doctors' engagement in online medical consultations, which is closely related to doctors' role behaviors (what one does). Thus, the identity theory is better for explaining the underlying mechanism of the impact of digital gifting on doctor engagement in OHC.

While prior studies have used identity theory as a theoretical framework to examine identity-related activities in computer-mediated communication, little is known about identity verification in OHCs. Our study extends the application of identity theory into the field of OHCs. Our results indicate that gift-giving in medical consultation can act as a way to recognize the role of a doctor and activate identity verification to motivate knowledge-sharing. Our findings also remind platform managers to pay closer attention to community features that can make doctors feel more recognized for their role activities.

Online Appendix J: Informal Payments and Doctors' Response Time

We examine the impact of the introduction of informal payments on doctors' response time. Specifically, we estimate the following regression specification:

$$AveResTime_{it} = d_i + \beta_0 + \beta_1 PostLaunch_t + \beta_2(PostLaunch_t \times ReceiveGift_{it}) + \beta_3 Controls + \varepsilon_{it}\ , \quad (\mathrm{J}.1)$$

where $AveResTime_{it}$ is our dependent variable representing the average response time (in days) of doctor *i* in time period *t*. From column 1 of Table J.1, we find that the coefficient on $PostLaunch_t$ is insignificant, which indicates that the introduction of the monetary gift feature does not have a significant effect on response time in general. One possible explanation is that the launch of this new feature does not significantly affect doctors' habits of using the platform. They may mainly use their spare time to engage the platform and respond to consultations as volunteers instead of paid work. However, column 2 of Table J.1 shows that doctors who actually receive gifts from patients will respond faster than those who do not because the coefficient on the interaction term is significantly negative. The reason could be that when receiving such monetary gifts, the focal doctors may feel more recognized for their knowledge-sharing activities. According to the identity theory (Stets and Serpe 2013), such identity verification motivates doctors to behave positively and pay more attention to the follow-up questions.

Table J.1. The Impact of the Introduction of the Monetary Gift Feature on Responses Time

Variables	AveResTime, FE	AveResTime, FE
PostLaunch	-0.017 (0.117)	0.026 (0.117)
PostLaunch×ReceiveGift		-0.143^{***} (0.050)
AveInterval	0.033^{***} (0.004)	0.032^{***} (0.004)
ThreadCount	-0.054^{***} (0.006)	-0.051^{***} (0.006)

AveQuesLen	0.001*** (0.000)	0.001*** (0.000)
AveConsNum	-0.097*** (0.012)	-0.095*** (0.013)
Weekly dummies	Yes	Yes
Observations	29,867	29,867

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are in parentheses.

Online Appendix K: Including Consultations after Offline Visits

To gain further insights, we include the consultations after offline visits into our dataset and conducted additional analyses. Specifically, in our consultation-level analysis, we add a dummy variable $AfterVisit_j$, which denotes patient status for each consultation thread j (1 represents consultations after offline visits, and 0 indicates ordinary online consultations without previous offline visits), into our regression models. The estimation results are reported in Table K.1. The coefficients on $AfterVisit_j$ are significantly negative, which indicates that doctors respond less to consultations after offline visits. One possible explanation is that the doctor has already met the patient offline and knows the patient's condition well. Therefore, the follow-up online communication will be more concise and direct than that with a first-time patient (a patient without offline visits).

Table K.1. The Impact of Digital Gifting on Doctors' Online Responses

Variables	DV: ResNum	DV: log(ResLen)
Explanatory Variable		
GiftOnly	0.438*** (0.016)	0.236*** (0.005)
LetterOnly	0.114*** (0.019)	0.043*** (0.006)
Gift&Letter	1.012*** (0.031)	0.361*** (0.009)
AfterVisit	**-0.467*** (0.009)**	**-0.135*** (0.003)**
Control		
ConsNum	0.481*** (0.000)	
log(ConsLen)		0.626*** (0.002)
ClinicDay	-0.009 (0.008)	-0.038*** (0.002)
Weekend	-0.002	0.004

	(0.009)	(0.003)
DiagFee	-0.002*** (0.000)	-0.001*** (0.000)
Tenure	-0.008*** (0.000)	-0.003*** (0.000)
ClinicTitle	Yes	Yes
Yearly dummies	Yes	Yes
Topic	Yes	Yes
Observation	917,217	917,217

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are provided in parentheses.

We also included the interaction term between digital gifting variables and patient status ($AfterVisit_j$) to examine how patient status moderates the impact of digital gifting on doctors' responses. The results are reported in the following table. We can see that the coefficients on the interaction terms are insignificant, suggesting that patient status does not significantly moderate the impact of digital gifting on doctors' responses. One possible explanation is that doctors' feelings of being appreciated and recognized might not depend on whether they have already met patients offline or not.

Table K.2. The Impact of Digital Gifting: Considering the Moderating Role of Patient Status

Variables	DV: ResNum	DV: log(ResLen)
Explanatory Variable		
GiftOnly	0.462*** (0.022)	0.248*** (0.008)
LetterOnly	0.122*** (0.047)	0.046*** (0.017)
Gift&Letter	1.151*** (0.068)	0.412*** (0.020)
AfterVisit	-0.461*** (0.009)	-0.133*** (0.004)
Interaction Term		
AfterVisit:GiftOnly	**-0.048 (0.031)**	**-0.015 (0.012)**
AfterVisit:LetterOnly	**-0.012 (0.051)**	**-0.003 (0.011)**
AfterVisit:Gift&Letter	**-0.156 (0.096)**	**-0.042 (0.037)**
Control		
ConsNum	0.481*** (0.000)	
log(ConsLen)		0.626*** (0.002)
ClinicDay	-0.009 (0.008)	-0.038*** (0.002)

Weekend	-0.002 (0.009)	0.004 (0.003)
DiagFee	-0.002*** (0.000)	-0.001*** (0.000)
Tenure	-0.008*** (0.000)	-0.003*** (0.000)
ClinicTitle	Yes	Yes
Yearly dummies	Yes	Yes
Topic	Yes	Yes
Observation	917,217	917,217

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are provided in parentheses.

We also find that, in general, patients have a higher probability of giving monetary gifts or nonmonetary thank-you letters to doctors in consultations after offline visits than in consultations without previous offline visits. Specifically, for consultations after offline visits, the probability that a patient sends a monetary gift to the doctor is 0.082 (the mean of *GiftOnly* when $AfterVisit_j = 1$). In contrast, for ordinary online consultations without prior offline visits, this probability is 0.046 (the mean of *GiftOnly* when $AfterVisit_j = 0$). For consultations after offline visits, the probability that a patient sends a nonmonetary thank-you letter to the doctor is 0.091 (the mean of *LetterOnly* when $AfterVisit_j = 1$). In contrast, for ordinary online consultations without prior offline visits, this probability is 0.009 (the mean of *LetterOnly* when $AfterVisit_j = 0$). For consultations after offline visits, the probability that a patient sends both a monetary gift and a nonmonetary thank-you letter to the doctor is 0.030 (the mean of *Gift&Letter* when $AfterVisit_j = 1$). In contrast, for ordinary online consultations without prior offline visits, this probability is 0.005 (the mean of *Gift&Letter* when $AfterVisit_j = 0$).

Online Appendix L: Spillover Effect of Informal Payments

We examine the spillover effect of informal payments on non-givers. Specifically, we focus on the spillover effect and exclude doctors' responses to patients who have given informal payments. Therefore, we introduce a new dependent variable, $AveResNumOther_{it}$, to represent the average number of responses of doctor *i* excluding those responses to patients who have given informal payment in time period t, which can capture the spillover effect. For example, suppose a doctor responds to five online consultations in a specific week and receives a gift in two of them. In that case, we will use the doctor's responses in the other three consultations to construct the dependent variable. Similarly, we use $\log(AveResLenOther_{it})$ to denote the logarithm of the average total response length in responses of doctor i excluding those responses to patients who have given informal payment in time period t. The regression specifications are as follows:

$$AveResNumOther_{it} = d_i + \beta_0 + \beta_1 PostLaunch_t + \beta_2 (PostLaunch_t \times ReceiveGift_{it}) + \beta_3 Controls + \varepsilon_{it}\,, \tag{L.1}$$

$$\log(AveResLenOther_{it}) = d_i + \beta_0 + \beta_1 PostLaunch_t + \beta_2 (PostLaunch_t \times ReceiveGift_{it}) + \beta_3 Controls + \varepsilon_{it}\,, \tag{L.2}$$

The coefficients on $PostLaunch_t$ are significantly negative, which is consistent with our main results and indicates a crowding-out effect of the introduction of informal payments. $PostLaunch_t \times ReceiveGift_{it}$ is the focal variable of interest. We find that the coefficients on this interaction term are significantly negative, which suggests a negative spillover effect on other patients. Specifically, when doctors receive monetary gifts, they tend to respond less to non-givers during the same time period: The average number of responses goes down by an additional 0.11, and the average response length decreases by an additional 4.9% for medical consultations from non-givers. A possible explanation is that since doctors mainly use their spare time to help patients in the OHC, they have limited time and energy. When they devote more effort to patients who have given monetary gifts, they will pay relatively less attention to non-givers.

Table L.1. The Spillover Effect of the Introduction of the Monetary Gift Feature

Variables	AveResNumOther, FE	log(AveResLenOther), FE
PostLaunch	-0.252*** (0.038)	-0.405*** (0.031)
PostLaunch×ReceiveGift	-0.111*** (0.023)	-0.049*** (0.012)
AveInterval	0.001 (0.001)	-0.004*** (0.001)
ThreadCount	0.009*** (0.002)	0.007*** (0.002)
AveQuesLen	0.000** (0.000)	-0.000*** (0.000)

AveConsNum	0.440*** (0.024)	
log(AveConsLen)		0.475*** (0.021)
Weekly dummies	Yes	Yes
Observations	28,601	28,601

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are in parentheses.

Online Appendix M: Social Comparisons Regarding the Number of Monetary Gifts

We investigate the effect of social comparisons among doctors regarding the number of informal payments. Specifically, we use the following regression specifications to consider the effect of social comparisons:

$$AveResTime_{it} = d_i + \beta_0 + \beta_1 MoreGift_{it} + \beta_2 PostLaunch_t + \beta_3 (PostLaunch_t \times ReceiveGift_{it}) + \beta_4 Controls + \varepsilon_{it}\,, \quad \text{(M. 1)}$$

$$\log(AveResTime_{it}) = d_i + \beta_0 + \beta_1 MoreGift_{it} + \beta_2 PostLaunch_t + \beta_3 (PostLaunch_t \times ReceiveGift_{it}) + \beta_4 Controls + \varepsilon_{it}\,, \text{(M. 2)}$$

where $MoreGift_{it}$ is a dummy variable indicating whether doctor *i* receives more monetary gifts than the 90th percentile of the number of gifts that doctors received in time period *t*. The reasons for choosing the 90th percentile are as follows: (1) The number of gifts received by doctors in a specific time period has a right-skewed distribution (the average number is 0.433); (2) Receiving more gifts than the 90th percentile of the number of gifts allows doctors to recognize that they are receiving significantly more gifts than other doctors. The estimation results are shown in Table M.2. We see that the coefficients on $MoreGift_{it}$ are insignificant, suggesting no significant social comparison effects across doctors regarding the number of informal payments. One possible explanation is that doctors do not observe the information regarding other doctors receiving informal payments and make comparisons. They have their own home pages in the online health community and respond to medical consultations that send to them. In other words, they do not know how many informal payments other doctors receive unless they check the home pages of other doctors one by one constantly.

Table M.2. The Social Comparison Effect of Informal Payments

Variables	AveResNum, FE	log(AveResLen), FE
PostLaunch	-0.240*** (0.037)	-0.402*** (0.031)
PostLaunch×ReceiveGift	0.104*** (0.015)	0.057*** (0.011)
MoreGift	0.010 (0.034)	0.003 (0.023)
AveInterval	-0.002* (0.001)	-0.005*** (0.001)
ThreadCount	0.006*** (0.002)	0.005** (0.002)
AveQuesLen	0.000** (0.000)	-0.000*** (0.000)
AveConsNum	0.452*** (0.022)	
log(AveConsLen)		0.491*** (0.020)
Weekly dummies	Yes	Yes
Observations	29,867	29,867

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Robust standard errors are in parentheses.

In addition, we investigate the autocorrelation between receiving informal payments. Specifically, we want to examine whether doctors who have accumulated informal payments before are more likely to receive them in the future. We split the posttreatment period into two halves. We calculate the number of informal payments that each doctor receives during the first half and the second half of the time period, respectively. If the autocorrelation phenomenon exists, we should observe that there is a positive correlation between the two numbers of informal payments. We compute the Pearson correlation coefficient and find a correlation coefficient of 0.772 with a *p*-value of 2.84e-145 (0.000), which tentatively suggests a positive correlation between the numbers of informal payments received. In other words, doctors who have accumulated informal payments before seem more likely to receive them in the future.

Online Appendix N: The Size of Monetary Payments and the Crowding-Out Effect

The average amount of monetary gifts doctors received in our data is 35.19 RMB (around 6 dollars), which is small compared to the income of doctors. The prior studies on behavioral economics find that the crowding-out effect mostly occurs when the monetary rewards are small instead of large (Gneezy and Rustichini 2000; Bénabou and Tirole 2006). For example, Gneezy and Rustichini (2000) conduct two controlled experiments, an intelligence quotient (IQ) experiment and a donation experiment, to test the effects of monetary incentives on performance. In the IQ experiment, an additional monetary reward per question answered correctly ranges from 0.1 NIS (0.03 dollars) to 3 NIS (0.9 dollars). In the donation experiment, the average additional reward a pair of participants receives is 1.5 NIS (0.45 dollars) for one treatment level and 21.9 NIS (6.53 dollars) for another treatment level. Their results show that the effect of small amounts of monetary incentives is detrimental to performance. Essentially, there is a discontinuity when introducing monetary incentives (illustrated by Figure N.1): Once a small monetary reward is introduced, the level of performance drops significantly. After that, the level of performance increases with the amount of monetary reward, implying that the crowding-out effect is more likely to occur when the monetary payments are small.

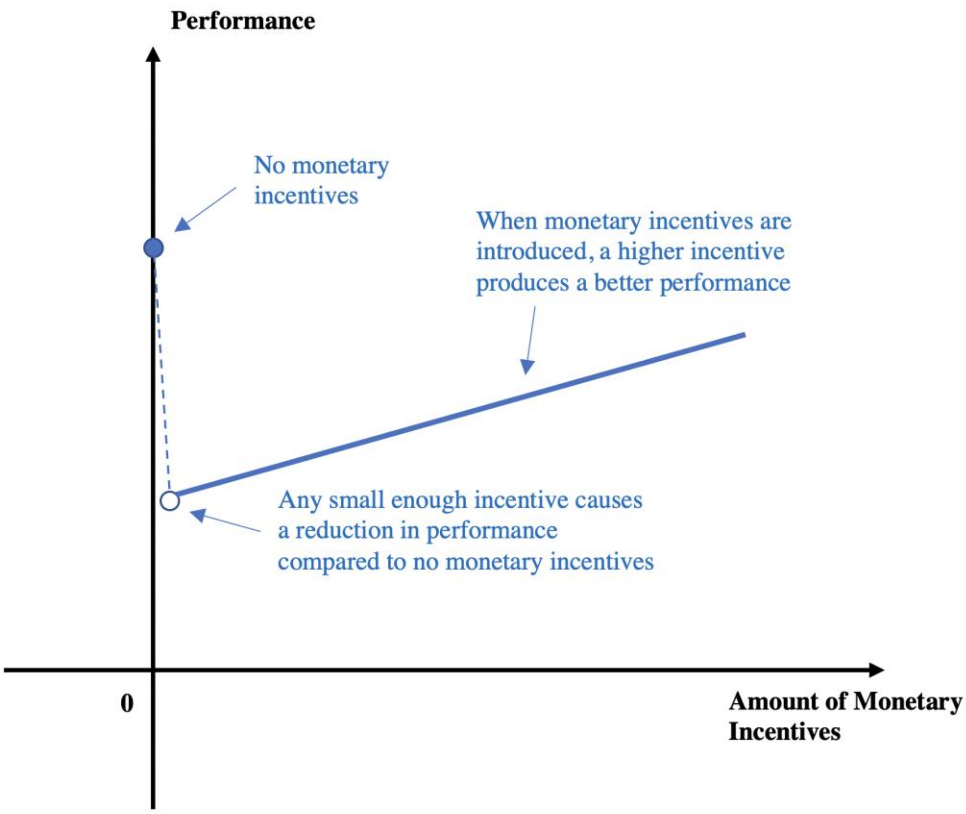


Figure N.1 Monetary Incentives and the Crowding-Out Effect

Online Appendix O: The Performance of the GSCM

To evaluate the performance of the GSCM, we first provide figures for comparison between treatment and synthetic control units. Specifically, we randomly select two treated units and provide a comparison between the treated units and the corresponding synthetic control units constructed based on GSCM. Each of the figures below displays the outcomes ($AveResNum_{it}$) of a treated unit and its corresponding synthetic control unit (The results for another dependent variable, $AveResLen_{it}$, are substantially similar). Specifically, the solid black line shows the outcome of the treated unit, while the blue dotted line represents the outcome of the synthetic control unit. We can see that, in both figures, $AveResNum_{it}$ of the synthetic control unit closely tracks the dynamics of that of the treated unit in the pretreatment period. The results suggest that the synthetic control unit can provide a reasonable counterfactual outcome for the treated unit.

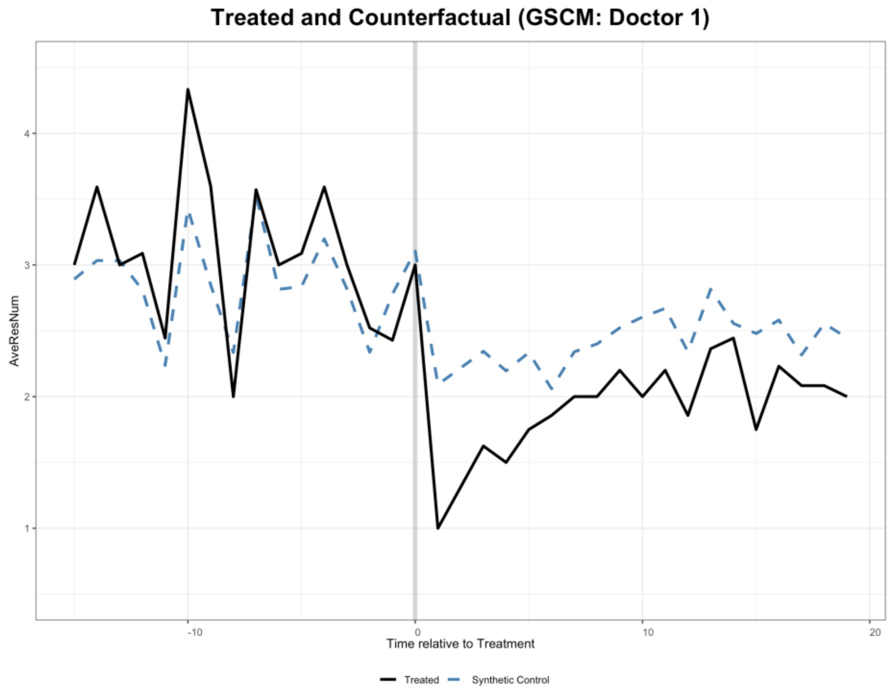


Figure O.1 (a). The Outcomes of the Treated and Synthetic Control Units

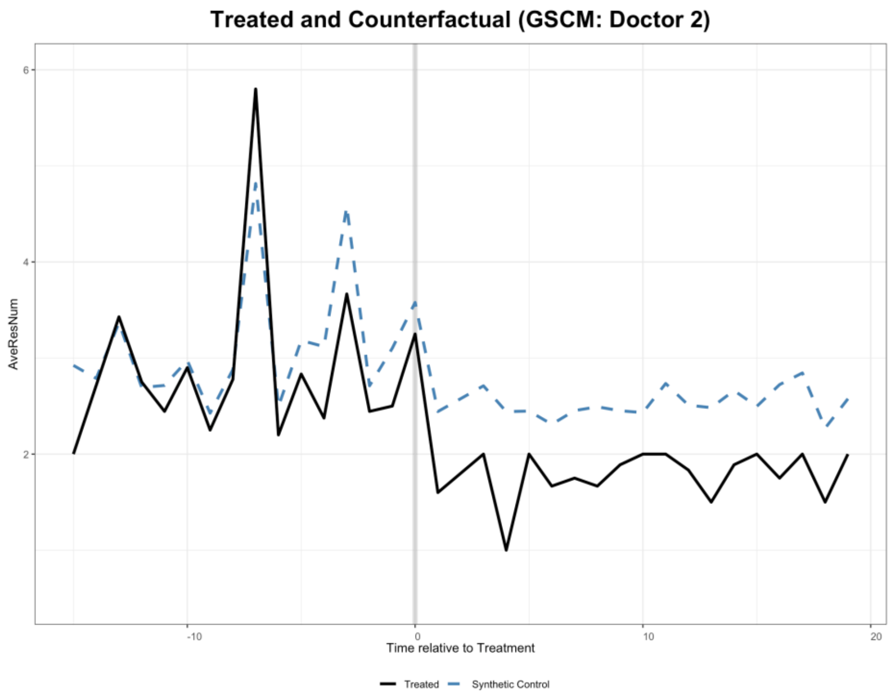


Figure O.1 (b). The Outcomes of the Treated and Synthetic Control Units

Second, we use the equivalence test proposed by Hartman and Hidalgo (2018) to examine the presence of a pretreatment trend. Specifically, we use the two-one-sided *t* (TOST) test. The test is considered passed if the average prediction error for any pretreatment period is within the equivalence range (Liu et al. 2022). The result of the equivalence test is shown in the figure below. We see that the average prediction error with 90% confidence intervals (the gray-shaded area) is within the equivalence range (the red dotted line). Thus, we can reject the null of inequivalence (equivalence test *p*-value is 0.005) and reckon that there exists no pretreatment trend. The test result indicates that a sufficient set of confounders has been controlled to address the endogeneity concerns and that GSCM provides a good control group.

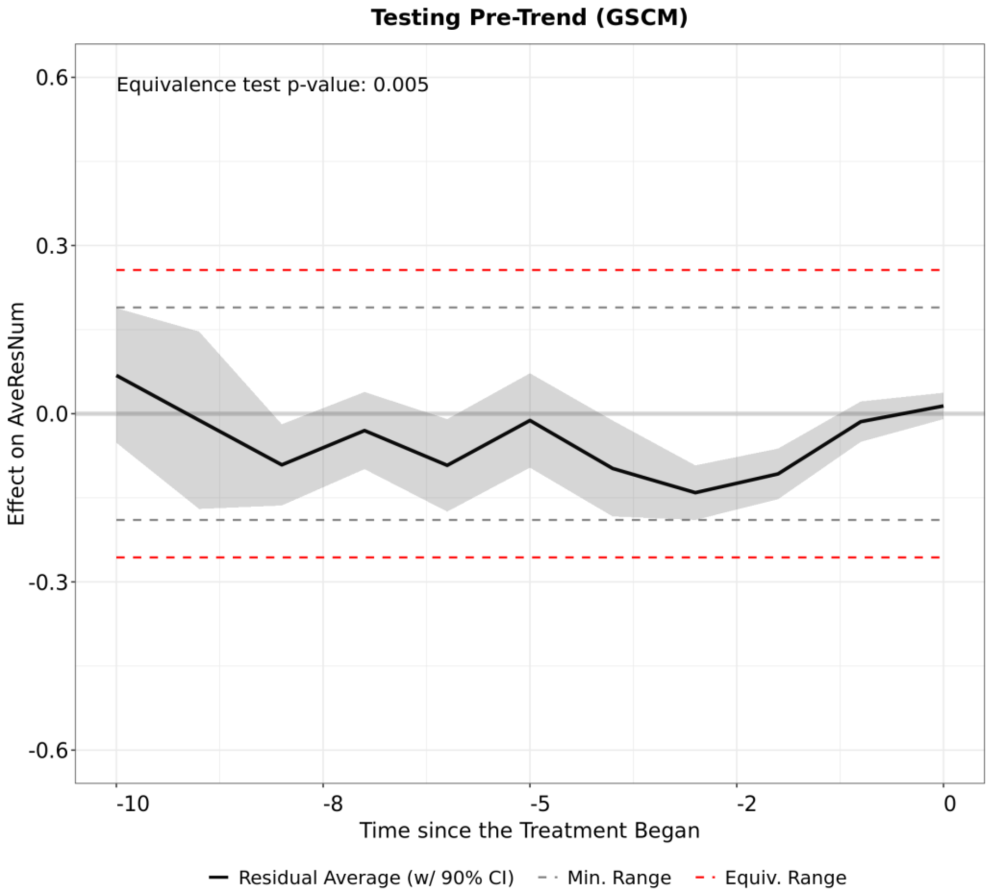


Figure O.2. Testing for no Pretreatment Trend

Online Appendix P: The Performance of the MCM

To evaluate the performance of the MCM, we first provide figures for comparison between the outcomes ($AveResNum_{it}$) of the treated units and the counterfactual outcomes generated by the MCM (the results for another dependent variable, $AveResLen_{it}$, are substantially similar). Specifically, the solid black line shows the outcome of the treated unit, while the blue dotted line represents the outcome of the synthetic control unit. We can see that, in both of the figures, the predicted counterfactual outcomes closely track the outcomes of the treated units in the pretreatment period. The results suggest that the MCM provides a reasonable counterfactual prediction for the treated units.

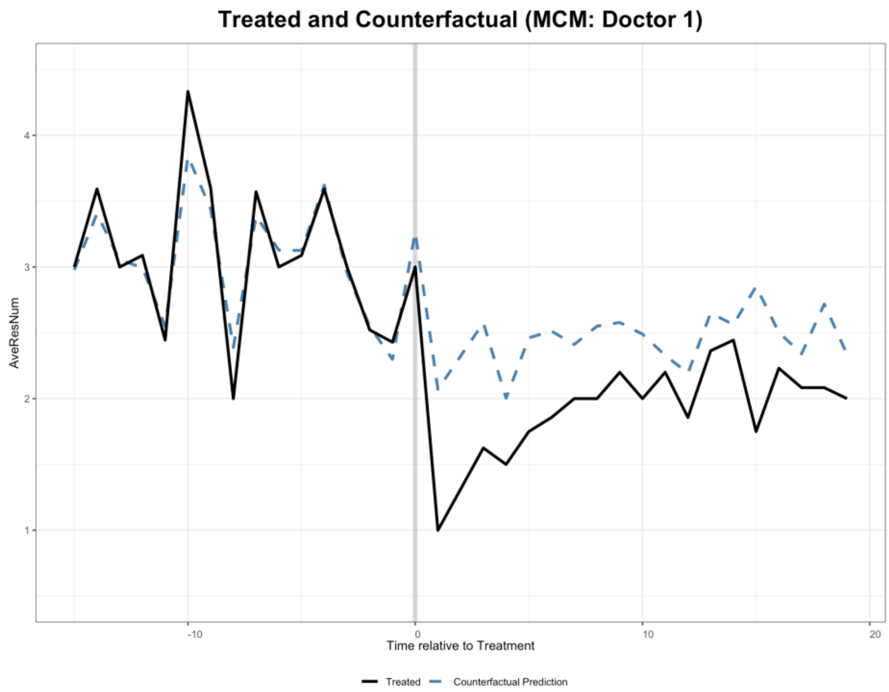


Figure P.1 (a). The Actual Outcomes and Counterfactual Outcomes

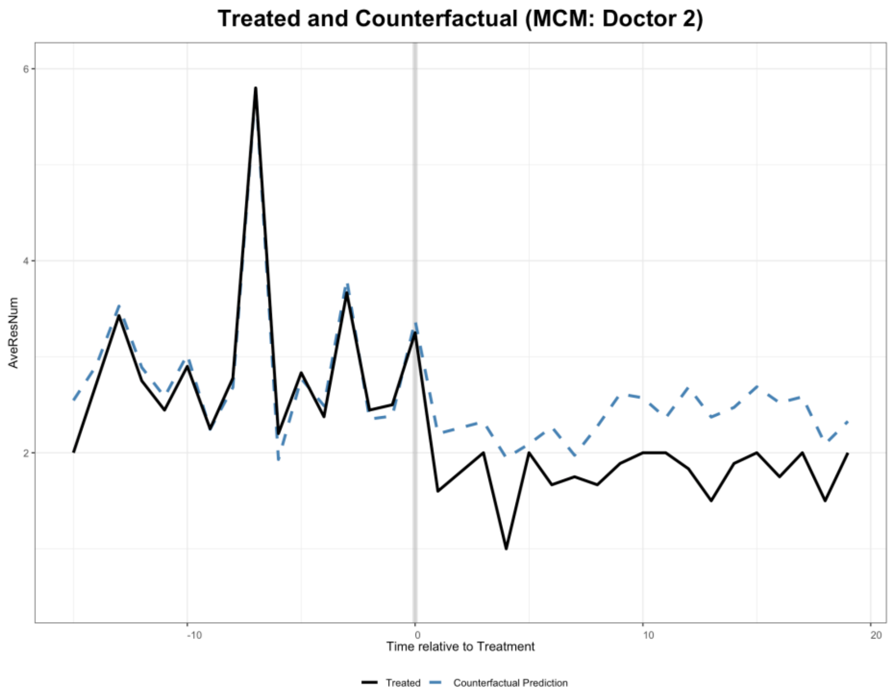


Figure P.1 (b). The Actual Outcomes and Counterfactual Outcomes

Second, we use the TOST equivalence test to examine the presence of a pretreatment trend. The result of the equivalence test is shown in the figure below. We see that the average prediction error with 90% confidence intervals (the gray-shaded area) is within the equivalence range (the red dotted line). Thus, we can reject the null of inequivalence (equivalence test p-value is 0.000) and reckon that there exists no pretreatment trend. The test result indicates that the MCM produces a reliable counterfactual outcome for the treated group.

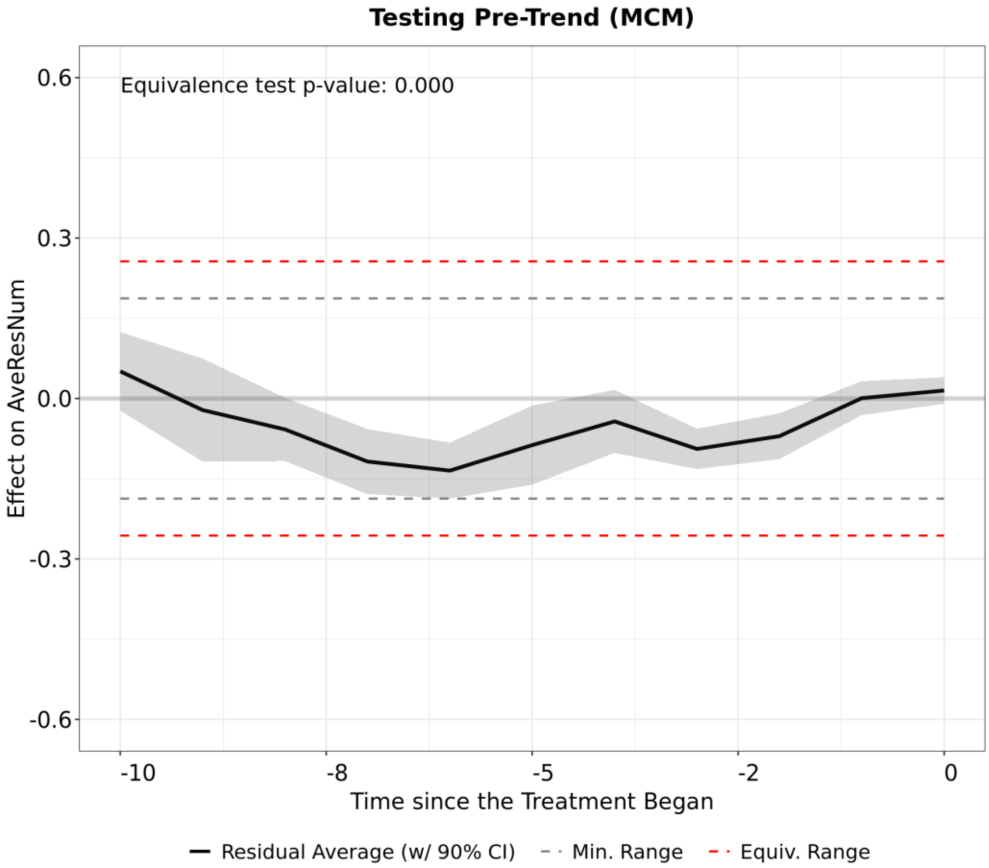


Figure P.2. Testing for no Pretreatment Trend

Online Appendix Q: The Performance of the PSM

As advised by Lechner (2002), we depict the distribution of propensity scores for the treatment and control groups before and after matching in Figure Q.1 to check the validity of the matching procedure. We find that the score distributions are substantially similar to one another after matching, which indicates that the two groups are well-matched. The result also suggests that the selection bias associated with observable covariates has been corrected.

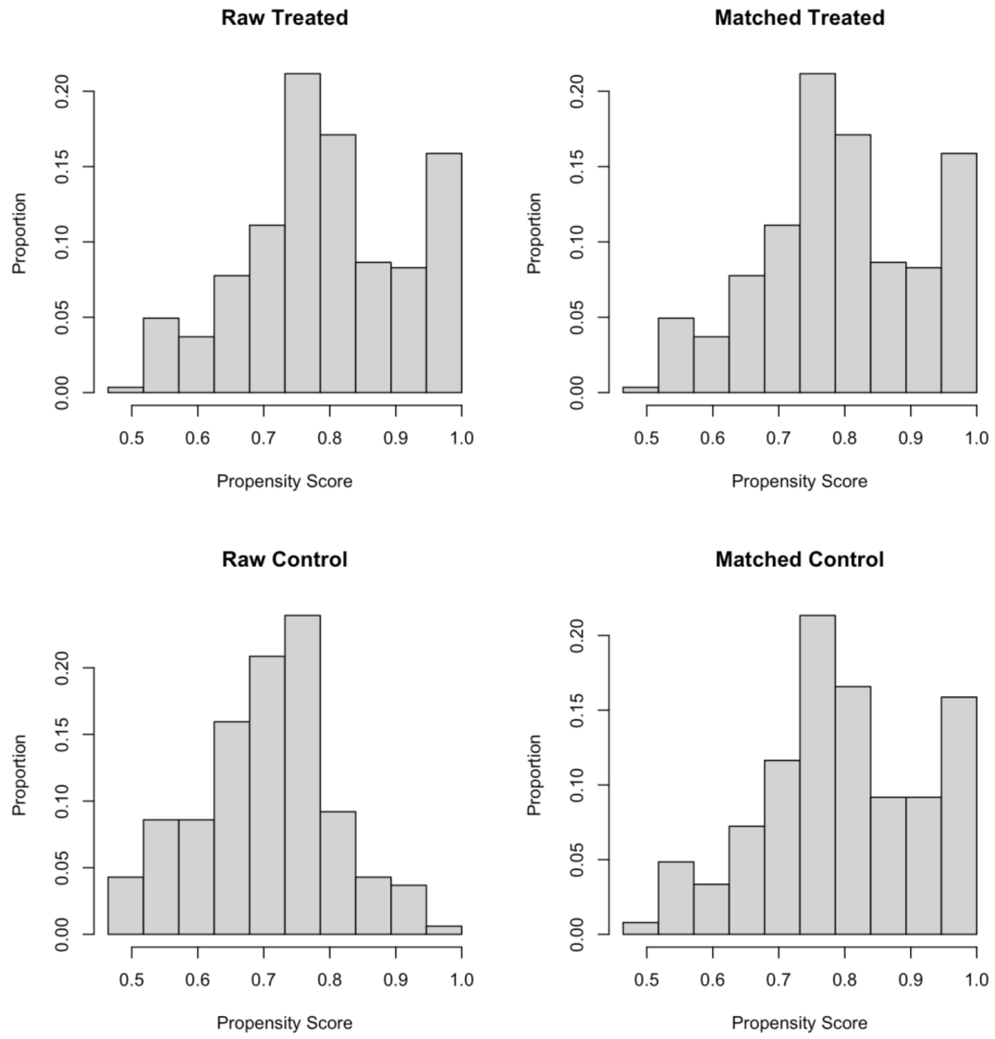


Figure Q.1. Distribution of Propensity Scores

Online Appendix R: Visual Representation of the Lead and Lagged Coefficients

Following Autor (2003) and Alyakoob and Rahman (2022), we provide a visual representation of the lead and lagged coefficients and their estimated confidence intervals in Figure R.1. The lead coefficients are close to zero, suggesting no parallel pretreatment trend.

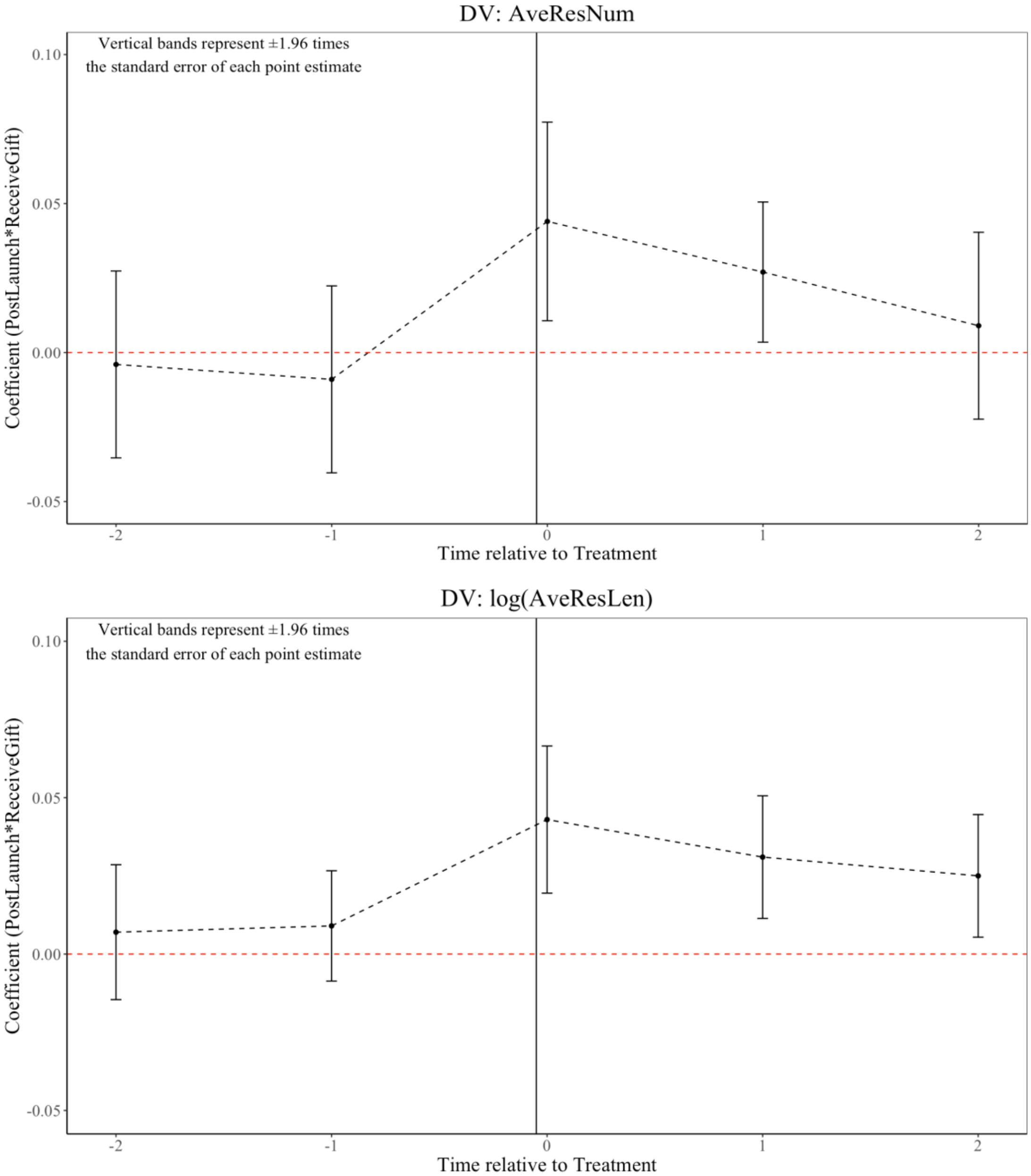


Figure R.1. Relative Time Model: Lead and Lagged Coefficients

Online Appendix S: Correlated Random Trend Model

We use the correlated random trend (CRT) model to rule out doctor-specific time trends as an alternative explanation for our findings. The CRT model can alleviate the concerns about the heterogeneous impact of time-varying characteristics on individual units. Following Wooldridge (2002, p.315) and Angrist and Pischke (2008, p.238), we use the following CRT models to control for doctor-specific trends:

$$AveResNum_{it} = d_i + \beta_0 + g_i t + \beta_1 PostLaunch_t + \beta_2 (PostLaunch_t \times ReceiveGift_{it}) \\ + \beta_3 Controls + \varepsilon_{it}\ , \qquad (S.1)$$

$$\log(AveResLen_{it}) = d_i + \beta_0 + g_i t + \beta_1 PostLaunch_t + \beta_2(PostLaunch_t \times ReceiveGift_{it}) + \beta_3 Controls + \varepsilon_{it}\ , \quad (S.2)$$

where g_i is a doctor-specific time trend for doctor i (from an estimation point of view, g_i is an unobserved factor, which is similar to the unobserved fixed effects). The CRT model includes both fixed effects and doctor-specific trends and thus can control for unobserved time effects that differ across doctors. It is worth noting that $g_i t$ can be correlated with the dependent variables, $AveResNum_{it}$ and $\log(AveResLen_{it})$, because $g_i t$ will be canceled out by first differencing Equations (S.1) and (S.2) twice. Thus, the estimation is unbiased. This feature makes the DID approach with correlated random trends more robust and convincing (Angrist and Pischke 2008). The estimation results of the correlated random trend models are reported in columns 1 and 2 of Table S.1. We can see that the results are consistent with our main results, which rule out doctor-specific time trends as an alternative explanation for our findings.

Table S.1. Robustness Checks: CRT Model and Using Shorter Time Window

Variables	(1) AveResNum, CRT	(2) log(AveResLen), CRT	(3) AveResNum, Small	(4) log(AveResLen), Small
PostLaunch	-0.181^{***} (0.027)	-0.346^{***} (0.053)	-0.194^{***} (0.032)	-0.352^{***} (0.027)
PostLaunch ×ReceiveGift	0.110^{***} (0.015)	0.033^{***} (0.010)	0.105^{***} (0.023)	0.053^{***} (0.011)
AveInterval	-0.000 (0.001)	0.004^{***} (0.002)	-0.004^{**} (0.002)	-0.008^{***} (0.001)
ThreadCount	0.003^{***} (0.001)	-0.002 (0.003)	0.007^{***} (0.002)	0.008^{***} (0.002)
AveQuesLen	0.000 (0.000)	-0.000^{***} (0.000)	0.000^{***} (0.000)	-0.000^{***} (0.000)
AveConsNum	0.445^{***} (0.021)		0.425^{***} (0.024)	
log(AveConsLen)		0.420^{***} (0.025)		0.473^{***} (0.029)

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Robust standard errors are in parentheses.

Online Appendix T: Eliminating Alternative Explanations

We try to eliminate alternative explanations by considering different treatment conditions. First, to reduce the possible impact of healthcare policy changes outside the online community, we extract a panel dataset with a shorter time window that covers the period from one year before the launch of the new feature to one year after and re-estimate the regression models using this sub-sample. In a shorter time window, our results are less likely to be affected by other healthcare policy changes. The results are presented in columns 3 and 4 of Table S.1 and are consistent with our main results. Thus, our findings are robust to a subsample that spans over a smaller period.

Second, we note that the research units in our context do not receive standard dummy treatment, which focuses on whether the unit has been treated. Doctors may receive multiple gifts from patients. Thus, we perform a robustness check using multivalued treatments. We replace the treatment indicator $ReceiveGift_{it}$ with $ReceiveGiftCount_{it}$, which denotes the number of monetary gifts doctor i receives from patients in time period t and re-estimate regression specifications (3) and (4). The estimation results are consistent with our main findings and are reported in columns 1 and 2 of Table T.1.

Third, considering that the amount of money gifted may have an impact on the outcomes of interest, we conduct another robustness check. We use $ReceiveGiftAmount_{it}$, which is calculated by adding the monetary value of all received gifts to represent the total amount of income from monetary gifts. Similarly, we re-estimate the regression models and show the results in columns 3 and 4 of Table T.1. Our findings are robust to considering the monetary value of gifts.

Table T.1. Eliminating Alternative Explanations: Multivalued Treatments and Monetary Value

Variables	(1) AveResNum, Multivalued Treatments	(2) log(AveResLen), Multivalued Treatments	(3) AveResNum, Monetary Value	(4) log(AveResLen), Monetary Value
PostLaunch	-0.216*** (0.014)	-0.400*** (0.011)	-0.212*** (0.014)	-0.399*** (0.010)
PostLaunch×ReceiveGift Count	0.023*** (0.008)	0.011** (0.006)		
PostLaunch×ReceiveGift Amount			0.000559*** (0.008)	0.000488*** (0.006)
AveInterval	-0.001 (0.001)	-0.005*** (0.001)	-0.001 (0.001)	-0.005*** (0.001)
ThreadCount	0.006*** (0.002)	0.005*** (0.001)	0.008*** (0.001)	0.005*** (0.001)
AveQuesLen	0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)
AveConsNum	0.473*** (0.004)		0.473*** (0.004)	

log(AveConsLen)		0.497^{***} (0.012)		0.497^{***} (0.012)
Weekly dummies	Yes	Yes	Yes	Yes
Observations	29,867	29,867	29,867	29,867

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Robust standard errors are in parentheses.

Fourth, when we look at the data further, we find that there are a few consultation threads in which the patient ended the consultation with a monetary gift. This suggests that, in such circumstances, the patient does not intend to give additional payments for healthcare services. Instead, the patient may want only to show appreciation and express his or her gratitude to the doctor. We conduct a robustness check by ruling out these ending gifts and by redefining the explanatory variables. We use a dummy variable, $ReceiveGiftNotEnd_{it}$, to indicate whether doctor i receives monetary gifts that are not ending gifts from patients in time period t. Similarly, $ReceiveGiftCountNotEnd_{it}$ is defined as a count variable. The estimation results are reported in Table T.2 and are also consistent with our main findings. The coefficients on the interaction term, ($PostLaunch_t \times ReceiveGiftNotEnd_{it}$), are still significantly negative, while those on $PostLaunch_t$ are still significantly negative. This suggests that after the launch of the monetary gift feature, doctors have contributed less to the OHC in general, but doctors who have actually received gifts that are not ending gifts from patients respond more actively to medical consultation questions than those who do not. Regression specifications that consider multivalued treatments of monetary gifts that are not ending gifts ($ReceiveGiftCountNotEnd_{it}$) produce similar results (columns 3 and 4 of Table T.2).

Table T.2. Eliminating Alternative Explanations: Ruling Out Ending Gifts

Variables	(1) AveResNum	(2) log(AveResLen)	(3) AveResNum	(4) log(AveResLen)
PostLaunch	-0.225^{***} (0.014)	-0.402^{***} (0.011)	-0.211^{***} (0.014)	-0.400^{***} (0.011)
PostLaunch×ReceiveGift NotEnd	0.082^{***} (0.018)	0.050^{***} (0.014)		
PostLaunch×ReceiveGift CountNotEnd			0.019^{**} (0.009)	0.019^{**} (0.008)
AveInterval	-0.001 (0.001)	-0.005^{***} (0.001)	-0.001 (0.001)	-0.005^{***} (0.001)

ThreadCount	0.007*** (0.001)	0.005*** (0.001)	0.007*** (0.002)	0.005*** (0.001)
AveQuesLen	0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)
AveConsNum	0.474*** (0.004)		0.473*** (0.004)	
log(AveConsLen)		0.500*** (0.012)		0.497*** (0.012)
Weekly dummies	Yes	Yes	Yes	Yes
Excluding ending gifts	Yes	Yes	Yes	Yes
Multivalued treatments	No	No	Yes	Yes
Observations	29,867	29,867	29,867	29,867

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are in parentheses.

Online Appendix U: Moderating Role of Social Status

We use the following moderated regression models to examine how the clinic title moderates the treatment effects.

$$\begin{aligned} ResNum_j = {} & \beta_0 + \beta_1 GiftOnly_j + \beta_2 LetterOnly_j + \beta_3 Gift\&Letter + \beta_4 ClinicTitle_j \\ & + \beta_5 (GiftOnly_j \times ClinicTitle_j) + \beta_6 \big(LetterOnly_j \times ClinicTitle_j\big) \\ & + \beta_7 \big(Gift\&Letter_j \times ClinicTitle_j\big) + \beta_8 Control_j + \varepsilon_j \,, \end{aligned} \tag{U.1}$$

$$\begin{aligned} \log\big(ResLen_j\big) = {} & \beta_0 + \beta_1 GiftOnly_j + \beta_2 LetterOnly_j + \beta_3 Gift\&Letter + \beta_4 ClinicTitle_j \\ & + \beta_5 (GiftOnly_j \times ClinicTitle_j) + \beta_6 \big(LetterOnly_j \times ClinicTitle_j\big) \\ & + \beta_7 \big(Gift\&Letter_j \times ClinicTitle_j\big) + \beta_8 Control_j + \varepsilon_j \,, \end{aligned} \tag{U.2}$$

The estimation results of the above model specifications with the clinic title as the moderating factor are shown in Table U.1.

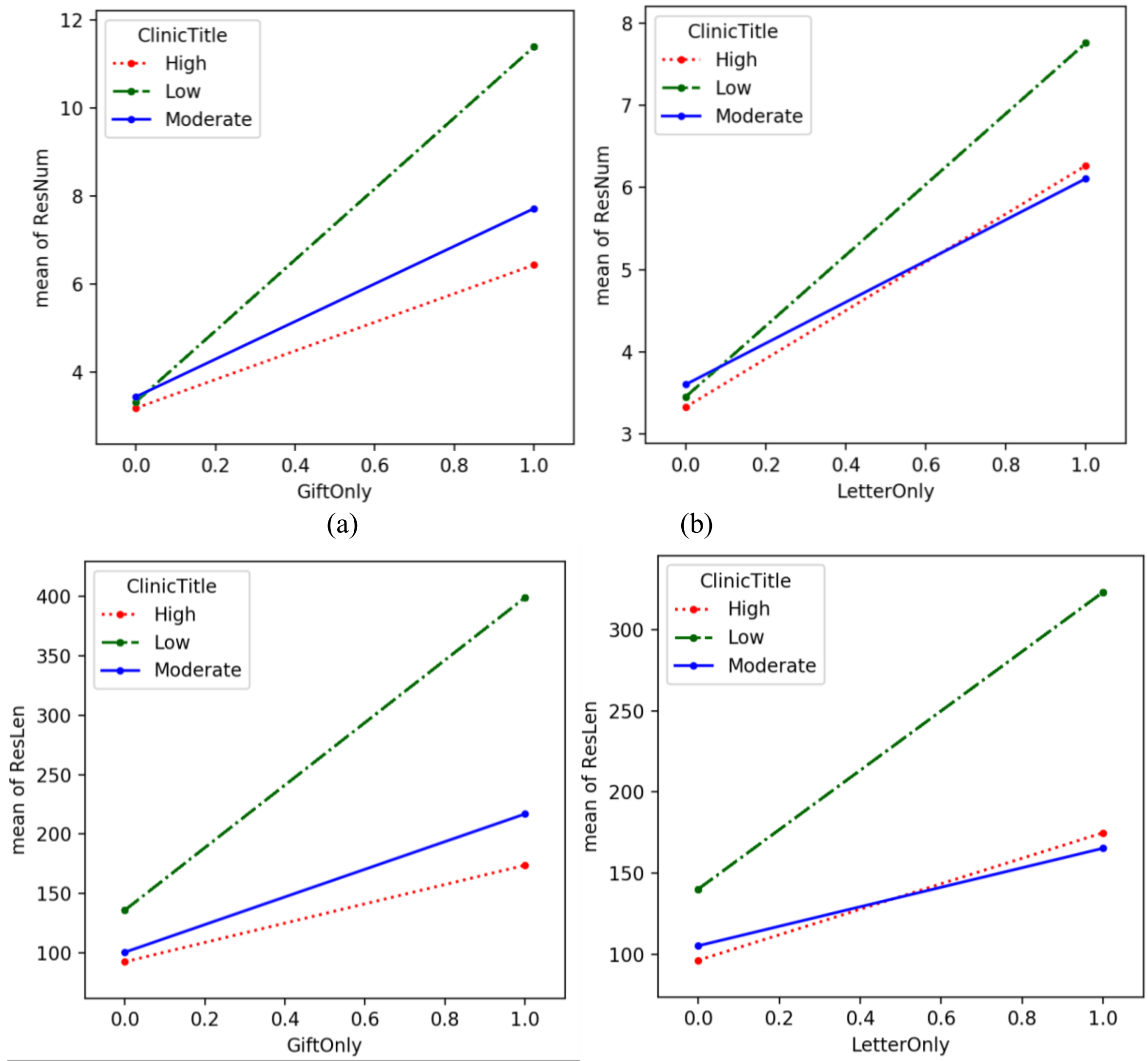
To help better interpret the interaction effect, we use interaction plots to graphically display the interaction effect between the impact of gifting options and different levels of the clinic title (see Figure U.1). An interaction plot is a helpful tool used to understand the interaction between two variables by illustrating all their possible combinations (Havakhor et al. 2019). Figure U.1(a) and Figure U.1(c) indicate that while giving a monetary gift has a positive impact on online responses in terms of both the number of responses and length of responses, the impact is relatively greater for doctors with lower-ranking clinic titles. However, Figure U.1(b) and Figure U.1(d) show that doctors respond differently toward nonmonetary gifts: Doctors with a high-ranking clinic title (chief physician) or low-ranking clinic title (resident physician) are more active in answering patients' inquiries upon receiving a thank-you letter than those with a moderate clinic title. The results suggest that a doctor's social status moderates the impact of digital gifting on his or her online responses.

Table U.1. The Impact of Digital Gifting: Considering the Moderating Role of Social Status

Variables	DV: ResNum	DV: log(ResLen)
Explanatory Variable		
GiftOnly	0.938*** (0.022)	0.255*** (0.007)
LetterOnly	0.297*** (0.032)	0.076*** (0.017)
Gift&Letter	1.460*** (0.067)	0.455*** (0.022)
Moderator		
ClinicTitle [High]	-0.029*** (0.006)	-0.091*** (0.002)
ClinicTitle [Low]	-0.185*** (0.022)	0.428*** (0.007)
Interaction Term		
ClinicTitle [High]:GiftOnly	-0.211*** (0.027)	-0.074*** (0.009)
ClinicTitle [Low]:GiftOnly	1.144*** (0.159)	0.130** (0.053)
ClinicTitle [High]:LetterOnly	0.403*** (0.062)	0.128*** (0.021)
ClinicTitle [Low]:LetterOnly	0.843** (0.373)	0.090*** (0.029)
ClinicTitle [High]:Gift&Letter	0.308*** (0.083)	0.012 (0.028)
ClinicTitle [Low]:Gift&Letter	0.708 (0.520)	0.363** (0.173)
Control		
ConsNum	0.471*** (0.000)	
log(ConsLen)		0.525*** (0.002)
ClinicDay	0.035*** (0.006)	0.009*** (0.002)
Weekend	0.028*** (0.007)	0.027*** (0.002)
DiagFee	-0.001*** (0.000)	-0.000** (0.000)
Tenure	-0.004*** (0.000)	-0.002*** (0.000)
ClinicTitle	Yes	Yes
Yearly dummies	Yes	Yes

Topic	Yes	Yes
Observations	630,419	630,419

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are provided in parentheses;



(a) (b) (c) (d)

Figure U.1. Interaction Plots of the Impact of Digital Gifting by Clinic Title Category

Our results show that social status has a moderating effect on the impact of digital gifting. With regard to monetary gifts, the impact of gifting on online responses weakens as social status improves. This could be because doctors with higher social status are also higher earners and, thus, less sensitive to monetary incentives. However, with regard to nonmonetary gifts, the moderating effect of social status is not simply one-directional. Doctors with either a high or a low social status respond more actively to medical consultation questions than those with a moderate social status. One possible explanation is that junior doctors may be more eager to become recognized experts and feel more valued for their contributions when they receive thank-you letters from patients. According to Maslow's hierarchy of needs (Maslow 1943), after each stage has been satisfied, senior doctors seek to satisfy the final stage: self-actualization. In other words, they have a desire for self-fulfillment and engage more actively when receiving gratitude and thanks. With regard to both monetary and nonmonetary gifts, the effect is similar to that of nonmonetary gifts. This could be because when receiving both monetary and nonmonetary gifts, the effect of nonmonetary gifts may dominate that of monetary gifts as the monetary value is not too high.

Online Appendix V: Including Doctor Fixed Effects

In this section, we include doctor fixed effects in our estimation because doctor information is available. Specifically, we have added doctor fixed effects into Equations (15) and (16) and re-estimated the regression models. The results are reported in Table V.1. We see that the results are substantially similar to our original estimation results, which suggests that our findings are robust when considering doctor fixed effects. In addition, we have included doctor fixed effects for other thread-level analyses and re-estimated the regression models. We find that our findings are all robust.

Table V.1. The Impact of Digital Gifting on Doctors' Online Responses

Variables	DV: ResNum	DV: log(ResLen)
Explanatory Variable		
GiftOnly	0.827*** (0.169)	0.189*** (0.011)
LetterOnly	0.589*** (0.159)	0.163*** (0.024)
Gift&Letter	1.636*** (0.438)	0.447*** (0.042)
Control		
ConsNum	0.471*** (0.026)	
log(ConsLen)		0.539*** (0.010)
ClinicDay	-0.006 (0.007)	-0.002 (0.002)
Weekend	0.006 (0.007)	0.021*** (0.002)
Tenure	-0.002*** (0.000)	-0.001*** (0.000)
Doctor FE	Yes	Yes
Yearly dummies	Yes	Yes
Topic	Yes	Yes
Observations	630,419	630,419

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors are provided in parentheses;

Online Appendix References

Alyakoob, M., & Rahman, M. S. (2022). Shared prosperity (or lack thereof) in the sharing economy. *Information Systems Research*, Forthcoming.

Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, *21*(1), 1-42.

Bellé, N. (2015). Performance-related pay and the crowding out of motivation in the public sector: A randomized field experiment. *Public Administration Review*, *75*(2), 230-241.

Bénabou, R., & Tirole, J. (2006). Incentives and prosocial behavior. *American Economic Review*, *96*(5), 1652-1678.

Bernal, J. L., Cummins, S., & Gasparrini, A. (2017). Interrupted time series regression for the evaluation of public health interventions: A tutorial. *International journal of epidemiology*, *46*(1), 348-355.

Curry, D. J., & Riesz, P. C. (1988). Prices and price/quality relationships: a longitudinal analysis. *Journal of Marketing*, *52*(1), 36-51.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. *Academy of Management Journal*, *50*(1), 25-32.

Exley, C. (2018). Incentives for prosocial behavior: The role of reputations. *Management Science*, *64*(5), 2460-2471.

Gneezy, U., & Rustichini, A. (2000). Pay enough or don't pay at all. *The Quarterly Journal of Economics*, *115*(3), 791-810.

Gorn, G. J., Tse, D. K., & Weinberg, C. B. (1991). The impact of free and exaggerated prices on perceived quality of services. *Marketing Letters*, *2*(2), 99-110.

Hartman, E., & Hidalgo, F. D. (2018). An equivalence approach to balance and placebo tests. *American Journal of Political Science*, *62*(4), 1000-1013.

Havakhor, T., Sabherwal, R., Steelman, Z. R., & Sabherwal, S. (2019). Relationships between information technology and other investments: A contingent interaction model. *Information Systems Research*, *30*(1), 291-305.

Jing, D., Jin, Y., & Liu, J. (2019). The impact of monetary incentives on physician prosocial behavior in online medical consulting platforms: Evidence from China. *Journal of Medical Internet Research*, *21*(7), e14685.

Kaplan, E. L., & Meier, P. (1958). Nonparametric estimation from incomplete observations. *Journal of the American Statistical Association*, *53*(282), 457-481.

Kwon, H. E., Dewan, S., Oh, W., & Kim, T. (2022). Self-regulation and external influence: The relative efficacy of mobile apps and offline channels for personal weight management. *Information Systems Research*, Forthcoming.

Lechner, M. (2002). Some practical issues in the evaluation of heterogeneous labour market programmes by matching methods. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *165*(1), 59-82.

Liu, L., Wang, Y., & Xu, Y. (2022). A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data. *American Journal of Political Science*, Forthcoming.

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review*, *50*(4), 370-396.

Salge, T. O., Antons, D., Barrett, M., Kohli, R., Oborn, E., & Polykarpou, S. (2022). How IT investments help hospitals gain and sustain reputation in the media: The role of signaling and framing. *Information Systems Research*, *33*(1), 110-130.

Stets, J. E., & Serpe, R. T. (2013). *Identity theory*. In Handbook of Social Psychology (pp. 31-60). Springer, Dordrecht.

Titmuss, R. M. (1970). *The gift relationship: From human blood to social policy*. London: Allen and Unwin.

Upton, W. E. (1973). *Altruism, attribution, and intrinsic motivation in the recruitment of blood donors*. Cornell University.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data MIT press*. Cambridge, MA.