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Quid pro quo in online medical consultation? Investigating the effects of small monetary gifts from patients

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Abstract

Recent years have seen robust growth in online medical consultation platforms. These platforms allow patients to access various healthcare services provided by doctors (e.g., health assessment, diagnosis, consultation, and supervision). In China, many such platforms allow patients to give small monetary gifts to doctors as an expression of gratitude. The implicit assumption is that expensive gifts influence doctors' medical service and generate conflicts of interest but small gifts do not. However, there is little empirical evidence to support this assumption. In order to fill this gap in the literature, our study investigates whether small gifts from patients impact the quality of service provided to the gift-givers (i.e., direct effect) and the nongivers (i.e., spillover effect). We examine three aspects of online medical service quality: (i) patient wait time, (ii) the amount of information in doctors' responses, and (iii) the degree of emotional support in doctors' responses. We find that despite the gifts' negligible monetary value, doctors who receive gifts do reciprocate to the gift-givers by providing them with more timely responses and greater emotional support. Furthermore, after receiving the small gifts, doctors may be slower in responding to nongivers and offer them less emotional support. We also investigate whether these effects (both direct and spillover effects) vary with doctors' backgrounds, including their professional experience and geographic location. Our findings have both theoretical and practical implications for patients, online medical consultation platforms, and healthcare policy makers.

KEYWORDS
fuzzy regression discontinuity design, gifts from patients, healthcare industry, online medical consultation, spillover effect

1 | INTRODUCTION

The question of how to provide fair access to high-quality healthcare is important in healthcare operations management (McCoy & Lee, 2014), and the existing literature shows that online healthcare markets provide a promising solution to this challenge (He et al., 2018). The global digital health market is expected to grow at a compound annual growth rate (CAGR) of over 20% between 2020 and 2024 (Technavio, 2020). In China, online medical consultation platforms are rapidly expanding, allowing patients to access various healthcare services (e.g., health assessment, diagnosis, consultation, monitoring, and medication and treatment plan updates) using different devices (e.g., PCs, smartphones, and tablets). Doctors nationwide can register with the platforms to provide these services, and patients can freely choose their providers (Liu et al., 2020). The online medical consultation market is expected to generate approximately 200 billion Chinese Yuan ($29 billion) in revenue by the end of 2020, which was considerably higher than anticipated prior to the beginning of the year (The Economist, 2020).

A common feature of these platforms is that patients can give small monetary gifts, typically worth about 10 Chinese Yuan (approximately $1.50), to doctors as an expression of gratitude (Zhang et al., 2018). A large number of patients have used this gift-giving feature. For example, on haodf.com, one of the largest platforms, more than 2 million patients have given approximately 4.1 million individual gifts to doctors as of June 2021.

This online gift-giving feature is a modern iteration of an age-old custom in China. While in the offline medical context, this practice has been under close scrutiny for a long

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time, online gifts to doctors have received little attention in the popular press or in academic research. A possible reason is that the monetary value of online gifts is negligible compared to that of offline gifts. For example, a Chinese patient may give a gift of 3000 Chinese Yuan (approximately $420) to his or her surgeon prior to a major operation (Yang, 2017). Such a gift naturally raises ethical concerns because it may be a strategy to elicit preferential treatment (Tu, 2019). In contrast, the much smaller online gifts may be simply viewed as genuine expressions of gratitude, which should not generate any negative consequences. Existing legal regulations and policies regarding patient gift-giving also seem to assume that only expensive gifts can influence doctors' behavior and generate conflicts of interest (Tu, 2019).

However, research in non-healthcare contexts yields evidence that even a small gift can have important impacts on gift recipients' behavior (e.g., Maréchal & Thöni, 2018). Allowing patients to give small gifts as an expression of gratitude is a well-meaning policy, but it is not uncommon for well-meaning policies to create unintended negative consequences. Therefore, our study examines whether small gifts from patients influence the quality of service provided by gift-receiving doctors in online healthcare.

1.1 | Motivation

Our study is motivated by the findings in experimental economics that small gifts may have large, unexpected impacts on gift recipients' behavior (Falk, 2007; Malmendier & Schmidt, 2017; Maréchal & Thöni, 2018). For example, a small gift increases the frequency of charitable donation by 17% (Falk, 2007). Similarly, sales representatives generate more than twice as much revenue when they give a small gift at the onset of their negotiations (Maréchal & Thöni, 2018). In the context of online medical consultation, patients typically consult a doctor multiple times over a short period of time. Given these repeated patient–doctor interactions, the seemingly innocuous small gifts may inadvertently influence the subsequent quality of service provided by the gift-receiving doctors.

There is also some discussion in prior research on the spillover effects of gifts, that is, the possibility that gifts may impact the quality of service received by nongivers (Grandhi & Grant-Kels, 2017). For example, after receiving a gift, a doctor may allocate less time to the care of nongivers. This possibility of negative spillover is a cause for concern because many online medical consultation platforms were founded with a mission of providing fair access to healthcare.[1] If gifts elicit preferential treatment at a cost to the nongivers, it defeats that purpose. Yet despite these apparent policy implications, spillover effects have also received little attention in empirical research. Even though our empirical context is Chinese online healthcare, understanding the effects of small gifts from patients on the quality of service provided to gift-givers and nongivers has broad policy implications for other contexts that involve gift-giving.

1.2 | Research questions and contributions

There is a call for research into operational issues related to online medical platforms in operations management (Kumar et al., 2018). Our study responds to the call by investigating the giving of small gifts from patients to their doctors, a prevalent practice that may impact medical service quality. We first seek to address the research question: (RQ1) *How do small gifts from patients impact the quality of service provided to gift-givers in online medical consultation (i.e., direct effect)?*

On the basis of prior literature and the current context of online medical consultation, we specifically examine three dimensions of service quality including patient wait time, the amount of information in doctors' responses, and the degree of emotional support in doctors' responses (Yan & Tan, 2014; Yang et al., 2019). Patient wait time, defined as the time a patient has to wait before being seen by a doctor, is an important dimension of medical service quality examined in the healthcare operations management literature (Cayirli & Veral, 2003; Salzarulo et al., 2011). Excessive wait time is a major reason for patient dissatisfaction (Salzarulo et al., 2011), and the timeliness of a doctor's response to patients in online medical consultation is even more important than it is in offline settings (Ko et al., 2019). Long wait times may lead patients to experience anxiety or make suboptimal decisions, both of which may exacerbate their medical condition (Yang et al., 2019).

Another important dimension of medical service quality is whether a doctor's response contains sufficient information (Hu et al., 2010). Responses with sufficient information can better help a patient understand and follow the doctor's advice, which may further contribute to the patient's recovery (Street et al., 2009). Medical service quality also has a socioemotional dimension (Naidu, 2009). Illness is typically accompanied by negative emotions such as fear and anxiety as a consequence of physical discomfort and lack of knowledge about the disease (McColl-Kennedy et al., 2017). Doctors' emotional support may alleviate the impact of these negative emotions by improving patients' confidence in coping with their illness (Zepeda & Sinha, 2016). Given the health implications of these different dimensions of medical service quality, our study investigates the effects of gifts from patients on each.

Different arguments can be made regarding the direct effects of gifts from patients. On the one hand, even a small gift may improve a doctor's overall affective state (Emmons & Crumpler, 2000), and there is evidence that positive affective states increase helping behavior (Bartlett & DeSteno, 2006). Gifts may also generate a "discipline" effect, that is, after receiving a gift from a patient, a doctor has an obligation to reciprocate to the patient with better medical care (Lambsdorff & Frank, 2010). Therefore, small gifts may have a positive direct impact on doctors' service quality. Furthermore, although the monetary value of a gift is small, many patients use these consultation platforms, and thus a doctor may receive a large aggregate amount of money from these small gifts. Hence, small gifts may serve as a meaningful extrinsic incentive, motivating doctors to provide better service to the gift-givers. On the other hand, according to the professional ethic of medicine, medical care should be given based on patients' needs rather than their ability to "buy" extra service (Lyckholm, 1998). One may argue that because of these professional ethics, doctors may not provide better service to the gift-givers (Drew et al., 1983). Given these competing arguments, our first research question seeks to ascertain whether small gifts from patients have direct effects on doctors' service quality.

Second, as previously discussed, gifts may generate a spillover effect on subsequent patients (Grandhi & Grant-Kels, 2017). This brings us to our next research question: (RQ2) *How do small gifts from patients impact the quality of service provided to the non-givers* (*i.e., spillover effect*)*?* On the one hand, as mentioned above, receiving gifts may improve a doctor's overall affective state, which may make them act more prosocially toward others, including the nongivers (Bartlett & DeSteno, 2006). On the other hand, monetary gifts may shift a doctor's mentality from a social mentality to a market mentality (Heyman & Ariely, 2004). Doctors with a market mentality treat their relationships with patients as economic exchanges. They will reciprocate to the gift-givers by providing better service quality, but for non-givers, they will only exert the least effort possible (Heyman & Ariely, 2004). Investigating the direction of these potential spillover effects clearly has important policy implications.

Furthermore, doctors on these online platforms differ in income, geographic location, and professional experience. Prior research suggests that the impact of monetary incentives varies with individual differences (Gneezy et al., 2011). On this basis, we might expect the effects of gifts from patients to vary based on individual characteristics. Therefore, we examine our third research question: (RQ3) *How do the effects of small gifts from patients vary with doctor characteristics?* Gifts, irrespective of their value, may change doctors' motivational states (Chang et al., 2012; Heyman & Ariely, 2004; Song et al., 2017), and this motivating effect may be strengthened or reduced by factors such as doctors' income and professional experience. A deep understanding of how the effects of gifts vary with doctor characteristics would have implications for evaluating online healthcare platforms' policies.

Our study thus contributes to both the literature and the policies related to online healthcare. While allowing the practice of giving small gifts as an expression of gratitude appears to be a policy based on good intentions, it may generate negative externalities for nongivers, and policies should be evaluated based on their outcomes rather than intentions. Through analyzing both the direct and spillover effects of small gifts, our study may provide useful guidance for online healthcare platforms and other health facilities to use in refining their policies. In the next section, we position our study in the broader literature in order to highlight our unique contributions.

2 | LITERATURE REVIEW

Medical service quality is a topic of great interest in the healthcare operations management literature (Bretthauer & Savin, 2018). Prior research examines different factors that may affect medical service quality in offline settings, including healthcare supply chain design (e.g., Rajapakshe et al., 2020; Sinha & Kohnke, 2009), appointment scheduling (e.g., White et al., 2011), patient priority schemes (e.g., Argon & Ziya, 2009), operational and clinical decision-making processes (e.g., Janakiraman et al., 2021; Laker et al., 2018; Senot et al., 2016), and hospital and patient incentive programs (e.g., Andritsos & Tang, 2018; Demirezen et al., 2016; Mehrotra & Natarajan, 2020). In the online context, service quality may be affected by a different set of factors, including doctors' or nurses' beliefs about online consultation (Ens et al. 2010), patient–doctor communication patterns (Henry et al., 2017), and technical aspects of online consultation (Miller, 2003). Our study focuses on the link between small gifts from patients, a specific feature of many online consultation platforms, and medical service quality.

In this section, we first review prior research on patients giving gifts to doctors in offline and online settings, respectively, and then discuss in detail how our paper differs. We also discuss other related practices that may impact medical service quality, again highlighting the contribution of our work. Figure 1 shows how our study is positioned in the literature.

2.1 | Gifts from patients in offline settings

Prior studies of patients giving gifts in offline settings focus on the social backgrounds of gift-giving patients (e.g., economic and cultural aspects) and on motives for the gifts (e.g., Gaal et al., 2006; Horodnic et al., 2018; Moldovan & Van de Walle, 2013). For example, Horodnic et al. (2018) investigate characteristics of patients who give expensive gifts. They find that patients who are unemployed, have a high tolerance for corruption, and are located in less affluent areas are more likely to give gifts. Moldovan and Van de Walle (2013) investigate people's attitudes toward patients giving gifts in Romania's healthcare sector. They find that people generally consider this practice to be ethically unacceptable. Gaal et al. (2006) suggest that gift-giving in Romania's healthcare sector is related to the shortage created by the highly centralized healthcare system formerly in place.

Most relevant to our work are a small number of studies that examine the consequences of gifts from patients. There are two streams of work in this body of literature. The first stream comprises studies that examine the direct effects of gifts on doctors' relationships with gift-givers and on the quality of treatments received by gift-givers. The second stream consists of studies that examine the externalities or spillover effects of gifts. We review both streams of work below.

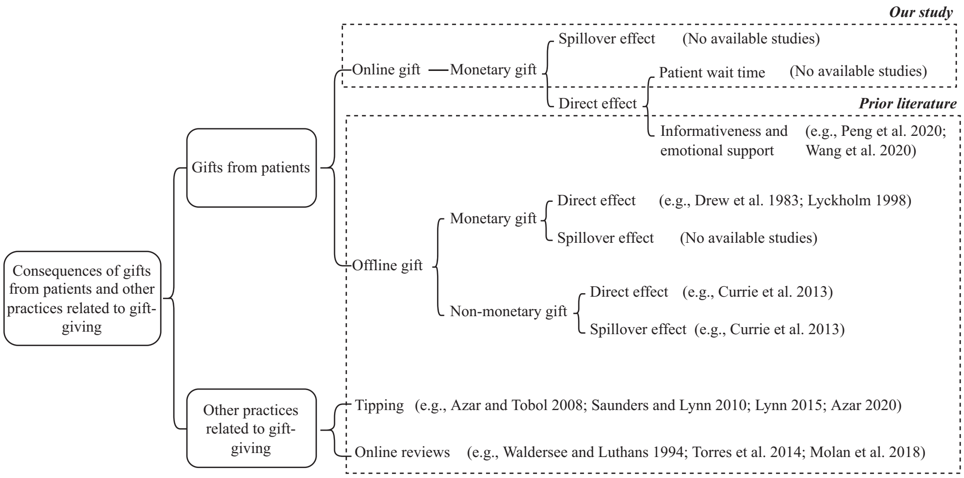

FIGURE 1 Positioning of our study in the existing literature

2.1.1 | The direct effects of gifts from patients

Although the practice of patients giving gifts to health professionals in offline settings has received much attention in the popular press, only a small number of studies investigate the effects of such gifts, and this stream of literature offers no consensus on whether they impact medical service quality. Koven (1998) argues that since gifts blur the professional boundaries between physicians and patients, gift-giving makes it difficult for doctors to treat their patients objectively—they may provide preferential treatment to the gift-givers. Similarly, Lyckholm (1998) argues that gifts from patients elicit a doctor's obligation to reciprocate, which subsequently motivates the doctor to provide better treatment. Mæstad and Mwisongo (2011) also argue that gifts positively affect quality of care because they may prompt doctors to exert more effort. Despite these arguments, Drew et al. (1983) show that in practice, doctors often do not reciprocate to the gift-givers because they think that spending extra time with or providing extra service to certain patients would disrupt their workflow. A more recent study also shows that doctors do not believe that gifts would make any difference to their medical practice (Tu, 2019).

Most of these studies are qualitative in nature. For example, Drew et al. (1983) asked a few doctors to keep diaries of gifts given by their patients. They then asked the doctors to recall their responses to the gift-givers. Similarly, Tu (2019) used a combination of observation (in hospitals) and interviews. Both Koven's (1998) and Lyckholm's (1998) findings are based on their own medical practice experiences. Though these qualitative studies generate valuable insight, they may suffer from social desirability and sampling biases. Since gift-taking may be of concern to the general public (Tu, 2019), gift-taking doctors may be less willing to participate in these studies, and those who do may be unlikely to say that their medical services are affected by gifts. In contrast, our study uses a large sample of observational data from an online medical consultation platform, which is less likely to suffer from social desirability and sampling biases.

2.1.2 | The spillover effects of gifts from patients

While a few studies investigate the spillover effects of gifts, most of them do not look at the healthcare context. For example, Abbink et al. (2002) run a stylized experiment where two players interact repeatedly and engage in gift exchange that may affect the general public. Malmendier and Schmidt (2017) examine gift exchange in a similar stylized experiment where the gift recipient makes decisions that may affect both gift-givers and nongivers. Both studies find that gifts affect the recipient's decision in favor of the gift-givers at the expense of the nongivers.

To the best of our knowledge, only one study investigates the spillover effects of gifts in healthcare. Currie et al. (2013) examine the impact of nonmonetary gifts on doctors' prescription of unnecessary antibiotics to gift-givers and nongivers who are close friends of the gift-givers. They find that gifts can create positive spillover effects when gift-givers are socially related to nongivers. Our study substantially differs from Currie et al. (2013) in the following respects.

First, we examine monetary gifts, whereas Currie et al. (2013) examine symbolic gifts that have little monetary value (i.e., a bookmark). Monetary gifts, like those we study, may qualitatively differ from symbolic gifts: motivation theories differentiate between extrinsic and intrinsic motivation (Bénabou & Tirole, 2006), and symbolic gifts are more likely to impact recipients' intrinsic motivation, whereas monetary gifts may impact recipients' extrinsic motivation. Second, Currie et al. (2013) examine a narrow situation where antibiotics are prescribed, and although antibiotic abuse is an important issue, antibiotics are not relevant to many diseases. Our study examines a set of broader outcomes (i.e., patient wait time, doctors' informativeness, and emotional support) that are relevant to most diseases in online medical consultation. Third, Currie et al. (2013) examine spillover effects experienced by patients who are socially close to gift-givers. In reality, many patients are not socially related, and our study investigates the spillover effects in this more general and common situation.

2.2 | Gifts from patients in online settings

A few recent studies have considered the consequences of patients giving gifts in online settings. For example, Peng et al. (2020) examine the impacts of gifts on the quality of service provided to gift-givers. They find that after receiving gifts, doctors provide more detailed responses to gift-givers. Wang et al. (2020) also find a positive link between gifts and doctors' informational and emotional support for the gift-givers. Jing et al. (2019) similarly find that monetary incentives are positively associated with doctors' prosocial behavior (i.e., providing free consultation).

Though these papers ask similar questions, there are important differences between them and our study. First, these studies only look at the direct effect of gifts, while our study examines both the direct and spillover effects. We study both effects because an exclusive focus on the direct effects may lead people to ignore the potentially detrimental spillover effects. Second, it is unclear if the findings from these studies can be interpreted causally because they are confounded by a number of alternative explanations. Our study seeks to rule out the alternative explanations and make credible causal inference. Third, these studies do not look at patient wait time, which is a primary reason for patient dissatisfaction (Salzarulo et al., 2011) and is considered an important dimension of medical service quality in the healthcare operations management literature (Cayirli & Veral, 2003; McColl-Kennedy et al., 2017).

2.3 | Other related practices that may impact service quality

Prior research has examined other related practices that may impact service quality. One of these practices is tipping in the service industries, which differs from the kind of gift-giving we study in two significant ways. First, motivations for online gift-giving and tipping are different. Existing research shows that future-service consideration is not a significant motivation for tipping (Azar, 2020). For example, people who tip in hotels or restaurants may not go back to the same places. Tipping is primarily motivated by a social norm as well as psychological considerations (e.g., avoiding feelings of guilt or embarrassment) (Azar, 2020). In contrast, a typical patient on an online consultation platform consults the same doctor multiple times, so their gift-giving may be motivated by future-service consideration. Second, tipping and gift-giving are practiced in different occupations. Lynn (2016) shows that customers are more likely to tip workers who are in low-wage, low-skill occupations, who deliver customized service, and whose performance can be easily evaluated. For example, people generally tip restaurant servers, bartenders, and taxi drivers, but not doctors, dentists, lawyers, or teachers (Lynn, 2016).

Another practice related to gift-giving is online reviews. Although both gifts and online reviews may impact service quality, they also differ in significant ways. First, motivations for online gift-giving and reviewing are different. The purpose of writing reviews is to provide feedback and share information with peer-customers. Once a review is submitted, it becomes publicly available to all visitors of an online platform. In contrast, gifts are only between a gift-giver and a recipient. Second, online reviews and gifts may impact service quality via qualitatively different mechanisms. Bénabou and Tirole (2006) suggest three sources of motivation: (i) extrinsic motivation is a material reward encouraging a person to perform a certain behavior, (ii) intrinsic motivation is a person's desire to perform the task for its own sake, and (iii) image motivation is a person's tendency to be motivated by others' perceptions. Monetary gifts are material rewards, which may primarily impact service quality via the extrinsic motivation route (Bénabou & Tirole, 2006). In addition, gifts allow patients to show appreciation to doctors. Doctors who receive gifts may feel happy and grateful, which will likely make their job more enjoyable. Hence, gifts may also impact service quality via the intrinsic motivation route. Moreover, given that small gifts are observable to the public, they may also play a part in a doctor's image motivation. Unlike monetary gifts, online reviews do not provide any direct material rewards to service providers. They may impact service quality via the intrinsic and image motivation routes. For example, a service provider might experience positive emotions when he or she sees praise, compliments, and gratitude in the reviews. Besides, because online reviews are visible to the public, positive comments in the reviews may improve a service provider's image.

In sum, gift-giving is fundamentally different from tipping and online reviews. Additionally, the research on tipping and online reviews focuses on the impact of these practices on service quality in general rather than on the quality of services provided to the specific people who perform the practice (e.g., reviewers or tippers). In contrast, our study examines service quality provided to gift-givers and nongivers. Due to these differences, insight from the tipping and online review literature does not directly inform our study.

3 | EMPIRICAL CONTEXT AND DATA

We collect data from haodf.com, a leading online medical consultation platform in China. Any licensed Chinese doctor can join the platform and set up a personal website with online consultation functions. As of June 2021, about 239,371 doctors had joined the platform. A doctor's personal website on the platform contains the doctor's professional and biographic information. Patients can browse doctors' information and request a consultation with any doctor of their choice. A consultation can be phone or text based, where a patient posts questions on a doctor's personal website and the doctor responds to the questions when he or she is available.[2] Our analysis focuses on text-based consultations (see Figure S1 for an example) because they make up most consultations on the platform and because data about phone-based consultations are not publicly available.

Patients need to pay a fee of approximately 100 Chinese Yuan (about \$15) on average for each consultation. Apart from this consultation fee, patients can voluntarily give a small monetary gift to their doctor (see Figure S2 for an example). Patients cannot freely decide the monetary value of a gift but can only choose from a few options provided by the platform (e.g., 5, 10, and 30 Chinese Yuan). The available gift options change frequently over time. The monetary value of gifts given to doctors is unobservable, but according to the platform, a gift typically has a value of 10 Chinese Yuan (about \$1.50). When a patient gives a gift to a doctor, the money gets transferred to the doctor's bank account, and the platform sends a notification to the doctor. The doctor can see the notification when logging on to the platform. In contrast with other contexts where gifts may be rejected (e.g., Krishnamurthy et al., 2014), doctors on the platform we study do not have the option of rejecting gifts.

We gathered detailed consultation records from 830 doctors who specialize in infertility (for both women and men) between April 2015 and April 2016. During this period, 259,870 patients consulted these doctors. A patient often consults a doctor multiple times over a short period of time (e.g., a week). A consultation consists of one or multiple questions posted by the patient at one time and the doctor's response to those questions, which is posted after a lag time (see Figures S1 and S2 for an example). Our dataset contains 592,699 consultations, including the content of patients' questions and doctors' responses and the times when these questions and responses were posted.

We also obtained records of gifts from patients, which contain whether and when each patient gave gifts to a doctor. The platform identifies doctors by name but anonymizes patient identities. We obtained doctors' information including their professional titles and geographic locations. Our analysis is performed at the consultation level; that is, we examine the effects of whether a patient gives gifts to a doctor prior to a consultation on the doctor's response to the consultation questions.

3.1 | Dependent variables

As discussed in Section 1.1, we examine three dimensions of service quality: patient wait time, doctors' informativeness, and doctors' emotional support. These are important dimensions of medical service quality drawn from the existing healthcare operations management literature (e.g., Cayirli & Veral, 2003; Hu et al., 2010; McColl-Kennedy et al., 2017). We create three variables, *wait*, *informativeness*, and *emotional*, to capture these three dimensions.

Patient wait time is defined as the time a patient waits before receiving a doctor's response. It is an important dimension of service quality in the healthcare operations management literature (Cayirli & Veral, 2003). Here, we measure patient wait time ($wait_{ijq}$) as the time (in hours) between patient i posting his or her questions and doctor j posting his or her response for consultation q.[3]

Informativeness is defined as the amount of information in a doctor's response to a patient's questions. It is also an important dimension of medical service quality (Hu et al., 2010). To measure doctors' informativeness ($informativeness_{ijq}$), we calculate the within-doctor z-scores based on the word count of doctors' responses. Specifically, we subtract the mean length of all of doctor j's responses to patients from doctor j's response to patient i for consultation q, then we divide this difference by the standard deviation of the length of doctor j's responses (Lowry et al., 2013).

Emotional support is a socioemotional dimension of medical service quality (Naidu, 2009), and it is defined as the degree to which a doctor's response contains emotional support (e.g., words of caring and sympathy). Emotional support ($emotional_{ijq}$) is measured by the number of times doctor j provides emotional support in his or her response to patient i for consultation q. We use natural language processing and supervised machine learning to identify whether each sentence in a doctor's response contains emotional support and count the number of sentences containing emotional support. To do so, we first randomly sampled 10,000 sentences in doctors' responses. We recruited five college students to label whether each of these sentences contains emotional support. We took an iterative approach to ensure that these sentences are labeled reliably. The five students first independently labeled all sentences. They then carefully examined the labeled sentences, discussed disagreements, and revised the disagreed labels until they found a common consensus. The labeled set was divided into a training (75%) and a test set (25%). The training set was used to build the classification model, and the test set was used to assess model performance.

We benchmarked two supervised learning algorithms, support vector machine (SVM) and random forest, against human labels. In terms of precision, recall, and F1-measure, the random forest classifier (92%, 93%, and 92%, respectively) outperforms the SVM classifier (72%, 88%, and 79%, respectively). Hence, we use random forest to process doctors' responses due to its superior performance. We count the number of sentences containing emotional support in doctor j's response to patient i for consultation q as a measure of $emotional_{ijq}$.

3.2 | Independent variables

To estimate the direct effect of gifts, we create an indicator variable $I(gift)_{ijq}$, which equals one if patient i gave at least

TABLE 1 Definitions of variables and summary statistics (N = 592,699)

	Variable	Definition	Mean	SD	Min	Max
Dependent variables	$wait_{ijq}$	The time interval (in hours) between patient *i*'s questions and doctor *j*'s response to the question for consultation *q*.	14.309	119.306	0	20,951
	$informativeness_{ijq}$	The standardized word count in doctor *j*'s response to patient *i*'s questions for consultation *q*.	0	0.999	–2.17	24.64
	$emotional_{ijq}$	The degree of emotional support doctor *j* provides to patient *i* for consultation *q*.	0.126	0.334	0	4
Independent variables	$I(gift)_{ijq}$	Whether patient *i* gave at least one gift to doctor *j* after consultation *q-1* but before consultation *q*.	0.019	0.137	0	1
	$I(otherGift)_{ijq}$	Whether doctor *j* received at least one gift from another patient after seeing patient *i*'s questions but before responding to those questions in consultation *q*.	0.084	0.278	0	1
Control variables	$offline_{ijq}$	Whether patient *i* had any offline consultations with doctor *j* before consultation *q*.	0.316	0.465	0	1
	$paid_{ijq}$	Whether doctor *j* waived the consultation fee of patient *i* for consultation *q*.	0.022	0.147	0	1
	$telephone_{ijq}$	Whether patient *i* communicated with doctor *j* over the phone before consultation *q*.	0.012	0.108	0	1
	$nPriorConsult_{ijq}$	The number of consultations between patient *i* and doctor *j* before consultation *q*.	2.193	1.507	1	10
	$record_{ijq}$	The number of medical test results or images that patient *i* uploaded for consultation *q*.	0.033	0.267	0	16
	$newTopic_{ijq}$	The number of new topics patient *i* raised in consultation *q* with doctor *j*.	0.336	0.473	0	4
	$askLength_{ijq}$	The word count of patient *i*'s questions in consultation *q* with doctor *j*.	78.023	69.863	1	1772
	$nQuestion_{ijq}$	The number of questions in patient *i*'s consultation *q* with doctor *j*.	1.339	0.777	1	18

Note: Some consultations started before our sampling period. Thus, the maximum patient wait time is longer than our data collection span.

one gift to doctor *j* after consultation *q*-1 but before consultation *q* and zero otherwise. To estimate the spillover effect of gifts, we create another indicator variable, $I(otherGift)_{ijq}$. If doctor *j* received at least one gift from another patient after seeing but before responding to a question from patient *i* during consultation *q*, this variable equals one. Otherwise, the variable equals zero.

3.3 | Control variables

Prior research shows that patients' past interactions with doctors may influence patient–doctor relationships, which may further impact doctors' service quality (Liu et al., 2007). Therefore, we control for a group of variables capturing patients' offline and past interactions with doctors. The controls include (i) whether patient *i* had any offline consultations with doctor *j* before consultation *q* ($offline_{ijq}$), (ii) whether patient *i* communicated with doctor *j* over the phone before consultation *q* ($telephone_{ijq}$), and (iii) the number of online consultations between patient *i* and doctor *j* prior to consultation *q* ($nPriorConsult_{ijq}$). Patients need to pay a fee for each consultation, but doctors may decide to waive the fee, and this decision may reflect the doctor's relationship with a patient. Therefore, we also control for (iv) whether doctor *j* waived the consultation fee of patient *i* for consultation *q* ($paid_{ijq}$). These controls allow us to proxy for patient-doctor relationships.

Prior research also suggests that doctors' responses are influenced by patients' questions (Shepherd et al., 2011). Therefore, we control for characteristics of patient questions, including (i) the number of medical test results or images that patient *i* uploaded for consultation *q* ($record_{ijq}$), (ii) the number of distinct topics patient *i* raised in consultation *q* with doctor *j* ($newTopic_{ijq}$),[4] (iii) the word count of patient *i*'s questions in consultation *q* with doctor *j* ($askLength_{ijq}$), and (iv) the number of questions in patient *i*'s consultation *q* with doctor *j* ($nQuestion_{ijq}$).[5] These controls allow us to proxy for the nature of the consultations (e.g., the complexity of the health issues in a consultation). The variables and descriptive statistics are summarized in Table 1.

4 | EMPIRICAL STRATEGIES AND ANALYSES

We use two different empirical strategies to estimate the direct and spillover effects of gifts. Both strategies address the potential endogeneity of patient gift-giving. Specifically, the association between patient gift-giving and doctors' service quality may not have a causal interpretation because it is confounded by alternative explanations. For example, both patient gift-giving and doctors' service quality can be driven by unobserved patient–doctor relationships: when a patient has a good relationship with a doctor, the patient is more likely to give gifts to the doctor, and the doctor is more likely to provide emotional support to the patient.

Our first empirical strategy employs ordinary least squares (OLS) estimation. To address the potential endogeneity issue, we identify alternative explanations that threaten the causal inference and run extra analyses to rule out these alternative explanations. Our second empirical strategy uses a regression discontinuity design (RDD). We exploit an event that exogenously increased the likelihood of patient gift-giving, which allows us to use a fuzzy RDD to estimate the effects of gifts in a narrow window around the event (Pinotti, 2017). We conclude the section by comparing the results from the fuzzy RDD with those from the OLS estimation.

4.1 | OLS estimation of the direct and spillover effects of gifts

We estimate the direct and spillover effects of gifts by running the following models:

$$\begin{aligned}\log(wait_{ijq}+1) &= patient\_doctor_{ij} + doctor_j + time_t \\ &\quad + \beta_1 \cdot I(gift)_{ijq} + \beta_2 \cdot I(otherGift)_{ijq} \\ &\quad + \sum_{m=1}^{6} \gamma_m \cdot I(gift)_{ij(q-m)} + X_{ijq} \cdot \delta + \varepsilon_{ijq}, \qquad (1)\end{aligned}$$

$$\begin{aligned}informativeness_{ijq} &= patient\_doctor_{ij} + doctor_j \\ &\quad + time_t + \beta_1 \cdot I(gift)_{ijq} + \beta_2 \cdot I(otherGift)_{ijq} \\ &\quad + \sum_{m=1}^{6} \gamma_m \cdot I(gift)_{ij(q-m)} + X_{ijq} \cdot \delta + \varepsilon_{ij}, \qquad (2)\end{aligned}$$

$$\begin{aligned}\log(emotional_{ijq}+1) &= patient\_doctor_{ij} + doctor_j \\ &\quad + time_t + \beta_1 \cdot I(gift)_{ijq} + \beta_2 \cdot I(otherGift)_{ijq} \\ &\quad + \sum_{m=1}^{6} \gamma_m \cdot I(gift)_{ij(q-m)} + X_{ijq} \cdot \delta + \varepsilon_{ijq}. \qquad (3)\end{aligned}$$

Here, i indexes patients, j indexes doctors, and q indexes consultations. We log patient wait time and emotional support to reduce the skewness of the two variables (e.g., Khuntia et al., 2018). Since patient wait time and emotional support can be zero, we add one to them before the transformation (e.g., Huang et al., 2020). The variable informativeness is a z-score, so we use the original scale in the analysis.

We include a series of fixed effects in the model. Specifically, $doctor_j$ is doctor fixed effects, which allow us to control for all observed or unobserved time-invariant doctor characteristics (e.g., doctors' medical expertise and personalities). $patient\_doctor_{ij}$ is patient–doctor pair fixed effects. The consultation platform anonymizes patients, but when a patient starts to consult a doctor, the platform assigns a numeric identifier to the patient–doctor pair. This is a unique identifier that will then apply to all future consultations between that particular patient and particular doctor. It is also in the URL of the pages that contain the consultations between the patient–doctor pair. By using this identifier, the platform avoids uniquely identifying the patient, since if the same patient consults a different doctor, that pair will receive a different identifier. As such, we add patient–doctor pair fixed effects rather than patient fixed effects to the models. These fixed effects allow us to control for time-invariant characteristics of the pair (e.g., patient–doctor relationships). Since consultations between a pair typically occur over a short period of time and are about the same medical issue, the fixed effects also control for the nature of patients' medical issues.

We also include $time_t$, a set of calendar fixed effects including hour of the day, day of the week, and month of the year when consultation q occurs, and whether consultation q occurs on a public holiday. We do this because the timing of a consultation may impact doctors' responses. For example, when a consultation question is posted when the doctor is working offline, the doctor may not immediately respond. The calendar fixed effects control for the seasonality of doctors' service quality and the effects of doctors' work schedules.

$I(gift)_{ijq}$ and $I(otherGift)_{ijq}$ are variables of primary interest that capture the direct and spillover effects of gifts from patients. $I(gift)_{ij(q\text{-}m)}$ is a series of lag variables for $I(gift)_{ijq}$, which measures whether patient i gave a gift to doctor j for prior consultations with doctor j ($m = 1, 2, \ldots, 6$).[6] These lag variables capture whether gifts associated with previous consultations have effects on the current consultation. X_{jiq} is a vector of control variables summarized in Table 1.

4.1.1 | Main results from OLS estimation

We first run a baseline model for each of the dependent variables. These baseline models contain the direct effect of a gift and the lagged effects of previous gifts, but do not contain spillover effects (see columns 1, 3, and 5 in Table 2). We then add the spillover effect term (see columns 2, 4, and 6 in Table 2) to the model. In all the models, we use robust standard errors clustered at the doctor level.

Table 2 shows that $I(gift)_{ijq}$ has a negative effect on patient wait time. The sign and size of the coefficients are consistent across all these models (see columns 1 and 2 in Table 2). Since we logged patient wait time, the coefficients are semielasticities. These coefficients show that gifts are associated with a 6.1% (i.e., $1 - e^{-0.063}$) to 6.5% (i.e., $1 - e^{-0.067}$) decrease in gift-givers' wait time.

Columns 3 and 4 in Table 2 show a nonsignificant effect of $I(gift)_{ijq}$ on doctors' informativeness. Columns 5 and 6 in

TABLE 2 Direct and spillover effects of gifts from patients

	Patient wait time		Informativeness		Emotional support	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
I(*gift*)	−0.063***	−0.067***	−0.029	−0.029	0.090***	0.090***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.009)	(0.009)
I(*otherGift*)		0.491***		0.018		−0.005
		(0.024)		(0.011)		(0.003)
$I(gift)_{-1}$	−0.008	−0.003	−0.007	−0.007	0.006	0.006
	(0.019)	(0.018)	(0.017)	(0.017)	(0.005)	(0.005)
$I(gift)_{-2}$	−0.009	−0.006	0.007	0.007	−0.011	−0.011
	(0.019)	(0.018)	(0.021)	(0.021)	(0.006)	(0.006)
$I(gift)_{-3}$	0.044	0.039	0.014	0.014	−0.002	−0.001
	(0.025)	(0.024)	(0.025)	(0.025)	(0.008)	(0.008)
$I(gift)_{-4}$	−0.017	−0.016	−0.021	−0.021	0.009	0.009
	(0.033)	(0.032)	(0.032)	(0.032)	(0.009)	(0.009)
$I(gift)_{-5}$	0.024	0.030	0.008	0.008	0.004	0.004
	(0.053)	(0.052)	(0.056)	(0.056)	(0.015)	(0.015)
$I(gift)_{-6}$	0.157	0.150	0.069	0.068	−0.022	−0.022
	(0.101)	(0.101)	(0.069)	(0.069)	(0.027)	(0.027)
offline	0.216***	0.208***	−0.039	−0.039	0.023**	0.023**
	(0.024)	(0.024)	(0.027)	(0.027)	(0.008)	(0.008)
paid	0.058*	0.053*	0.292***	0.291***	0.001	0.001
	(0.024)	(0.023)	(0.029)	(0.029)	(0.005)	(0.005)
telephone	−0.142	−0.141	−0.315***	−0.315***	0.051***	0.051***
	(0.073)	(0.074)	(0.064)	(0.064)	(0.013)	(0.013)
record	−0.092***	−0.090***	0.001	0.002	0.010**	0.010**
	(0.009)	(0.009)	(0.011)	(0.011)	(0.003)	(0.003)
newTopic	0.149***	0.144***	0.197***	0.197***	−0.009	−0.009
	(0.023)	(0.023)	(0.037)	(0.037)	(0.006)	(0.006)
nQuestion	0.112***	0.107***	0.014*	0.014*	−0.006***	−0.005***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)
askLength	0.001***	0.001***	0.002***	0.002***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
nPriorConsult	0.003	0.005	−0.036***	−0.036***	0.005***	0.005***
	(0.005)	(0.004)	(0.006)	(0.006)	(0.001)	(0.001)
F-value	56.1	73.3	57.5	55.7	21.2	20
Observations	592,699	592,699	592,699	592,699	592,699	592,699

Note: (1) All models include doctor fixed effects, patient-doctor pair fixed effects, and time fixed effects including hour of the day, day of the week, and month of consultation q, and whether consultation q was on a holiday. Robust errors (in parentheses) are clustered at the doctor level. (2) *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 2 show a positive effect of $I(gift)_{ijq}$ on doctors' emotional support. These coefficients show that gifts are associated with a 9.4% (i.e., $e^{0.090} - 1$) increase in emotional support to gift-givers. None of the lagged terms are significant (see columns 1, 2, 3, 4, 5, and 6 in Table 2). This suggests that gifts associated with previous consultations have no effect on the current consultation. These findings speak to our first research question, the direct effects of gifts from patients.

Table 2 shows that $I(otherGift)_{ijq}$ has a positive effect on patient wait time (see column 2 in Table 2). The coefficient shows a 63% (i.e., $e^{0.491} - 1$) increase in a nongiver's wait time if other patients gave gifts to the doctor.[7] Columns 4 and 6 in Table 2 show that $I(otherGift)_{ijq}$ has no significant effect on doctors' informativeness or emotional support. These findings speak to our second research question, the spillover effects of gifts from patients.[8]

The findings from the OLS models (see Table 3) suggest that smal4 gifts from patients may decrease the gift-givers' wait time and increase doctors' emotional support for the gift-givers, but that they have no significant effect

TABLE 3 Summary of ordinary least squares (OLS) findings for RQ1 and RQ2

	Patient wait time	Informativeness	Emotional support
Direct effects (RQ1)	Decrease	Nonsignificant	Increase
Spillover effects (RQ2)	Increase	Nonsignificant	Nonsignificant

TABLE 4 Subsample analysis of the spillover effect on doctors' emotional support

	Subsamples based on doctors' average level of emotional support				
	Quantile 0–20	Quantile 20–40	Quantile 40–60	Quantile 60–80	Quantile 80–100
	0–0.055	0.055–0.086	0.086–0.117	0.117–0.164	0.164–0.883
	(1)	(2)	(3)	(4)	(5)
I(gift)	0.053*	0.042***	0.094***	0.117***	0.110***
	(0.022)	(0.010)	(0.017)	(0.021)	(0.018)
I(otherGift)	0.003	0.001	−0.002	−0.000	−0.017**
	(0.002)	(0.005)	(0.003)	(0.005)	(0.005)
F-value	14.2	12.2	17	41.5	17.4
Observations	61,082	136,626	142,471	129,287	123,233

Note: (1) All controls, lag variables for $I(gift)_{ijq}$, and fixed effects from Equation (3) are included but not reported. Robust errors (in parentheses) are clustered at the doctor level. (2) *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

on doctors' informativeness. A possible reason for this finding is that doctors' informativeness may be primarily driven by the nature of patients' questions. For example, a lengthy question about a relatively complex illness may lead to more detailed responses. Indeed, our analysis shows that the length of patients' questions (captured by the control variable *askLength*) has a positive effect on doctors' informativeness (see Table 2).

Our findings also suggest that small gifts from patients may have a spillover effect that increases nongivers' wait time. We run a Wald test to compare the sizes of the direct and spillover effects. The test shows that the spillover effect of gifts on patient wait time is significantly larger than its direct effect (−0.067 vs. 0.491, chi-square = 265, p-value < 0.001). Recall that on average, it takes about 14.3 h for a doctor to respond to patients' questions (see Table 1). A gift from a patient is associated with a reduction in gift-givers' wait time to 13.4 h (i.e., $14.3 \times e^{-0.067}$), but it is associated with an increase in nongivers' wait time to 23.4 h (i.e., $14.3 \times e^{0.491}$). This rough estimation shows that the spillover effect of gifts from patients might be more concerning than the direct effect.

We do not find any spillover effect of gifts on doctors' informativeness or emotional support. The nonsignificant spillover effect of gifts on doctors' emotional support is likely due to a floor effect: while gifts may elicit doctors' emotional support for gift-givers, they may not reduce doctors' emotional support for nongivers because the level of such support is already low. Our analysis shows that the average number of times doctors provide emotional support in their responses is only 0.126 (see Table 1). This is consistent with existing research showing that in offline consultations, Chinese doctors typically do not offer emotional support to their patients (Tu, 2019; Yang, 2017).

To examine whether this finding is due to a floor effect, we rerun (Equation 3) on subsamples created based on doctors' average level of emotional support. If the finding is driven by a floor effect, gifts should have a significant spillover effect on emotional support for doctors who provide more emotional support on average. We calculate the mean of emotional support for each doctor and split the sample into five subsamples based on the quantiles of doctors' mean value of emotional support. We find that the spillover effect of gifts on doctors' emotional support is nonsignificant for doctors who provide low levels of emotional support (see columns 1, 2, 3, and 4 in Table 4). However, for the top 20% of doctors who provide the highest emotional support, gifts have a significant negative spillover effect (see column 5 in Table 4).

Overall, the findings from the OLS analysis provide preliminary evidence to address the question of whether small gifts have impacts on quality of service provided to gift-givers and nongivers. However, the OLS estimators do not have a causal interpretation as they are confounded by a number of alternative explanations. We investigate these alternative explanations in the next sections.

4.1.2 | Alternative explanation for the direct effect of gifts

As discussed earlier, a potential endogeneity issue is that the link between gifts from patients and doctors' service quality may be confounded by a third variable, the patient–doctor relationship. Drew et al. (1983) suggest that patients are more likely to give gifts to their doctor if they have a good relationship with that doctor. There is also an abundance of evidence showing that doctors are more likely to provide better service if there is a high-quality patient–doctor relationship (e.g., Chipidza et al., 2015; Moore et al., 2004). Therefore, an alternative explanation for the OLS estimate of the direct effect is that both patient gift-giving and doctors' service quality are driven by the patient–doctor relationship, so the link between them is merely correlational rather than causal.

We may test this alternative explanation by controlling for patient–doctor relationships in OLS regressions. If the OLS estimator only captures a correlation, adding patient–doctor relationships as a control will render the effect of gifts nonsignificant. However, one challenge is that patient–doctor relationships are not observable. While the patient–doctor fixed effects in Equations (1–3) do allow us to control for time-invariant patient–doctor relationships, in reality these relationships may be time varying. For example, a relationship may strengthen over time as a patient and a doctor interact with each other repeatedly. Based on the suggestion that a good patient–doctor relationship is revealed as a patient's preference for seeing a doctor repeatedly over time (Ridd et al., 2009), we also use the number of times a patient consulted a doctor prior to the current consultation (i.e., $nPriorConsult_{ijq}$ in Equations 1–3) as a proxy for patient–doctor relationships in the OLS models.

However, one may argue that the linear effect of the number of prior consultations may not effectively capture the effect of patient–doctor relationships. Therefore, we run an OLS regression with a quadratic term of $nPriorConsult_{ijq}$ to capture the nonlinearity of the number of prior consultations.

$$\begin{aligned} &serviceQuality_{ijq} \\ &= patient\_doctor_{ij} + doctor_j + time_t + \beta_1 \cdot I(gift)_{ijq} \\ &\quad + \beta \cdot I(otherGift)_{ijq} + \sum_{m=1}^{6} \gamma_m \cdot I(gift)_{ij(q-m)} + X_{ijq} \cdot \delta \\ &\quad + \theta \cdot nPriorConsult_{ijq} + \rho \cdot nPriorConsult_{ijq}^2 + \varepsilon_{ijq}. \end{aligned} \tag{4}$$

The results show that adding the quadratic term does not materially change the direct and spillover effects of gifts from patients (see columns 1, 3, and 5 in Table S4).

In addition to the OLS regression with a quadratic term, we further run a piecewise regression that specifies a breakpoint a priori based on a unique feature of the online consultation platform: the fact that each patient's first three consultations with a doctor are free of charge. After these free consultations, the patient has to pay a fee for each further consultation with the same doctor. Alternatively, the patient can switch to a different doctor to receive three more free consultations. Therefore, if a patient chooses to pay a doctor for additional consultations rather than switch to a new doctor for free service, this is an indication of a good patient–doctor relationship (Liu et al., 2020). It then stands to reason that the patient-doctor relationship may be qualitatively different before and after the three free consultations. The following piecewise regression allows the number of prior consultations to have different effects before and after the three free consultations:

$$\begin{aligned} &serviceQuality_{ijq} \\ &= patient\_doctor_{ij} + doctor_j + time_t + \beta_1 \cdot I(gift)_{ijq} \\ &\quad + \beta_2 \cdot I(otherGift)_{ijq} + \sum_{m=1}^{6} \gamma_m \cdot I(gift)_{ij(q-m)} + X_{ijq} \cdot \delta \\ &\quad + \lambda \cdot nPriorConsult_{ijq} + \pi \cdot (nPriorConsult_{ijq} - 3) \\ &\quad \cdot I(nPriorConsult_{ijq} > 3) + \varepsilon_{ijq}. \end{aligned} \tag{5}$$

Here, $I(nPriorConsult_{ijq} > 3)$ is an indicator variable, which equals one if patient i has consulted doctor j more than three times prior to consultation q and zero otherwise. The parameters λ and π allow the number of prior consultations to have different effects before and after the three free consultations (these effects are λ and $\lambda + \pi$, respectively).[9] Again, the piecewise regression does not materially change the direct and spillover effects of gifts (see columns 2, 4, and 6 in Table S4). Therefore, we conclude that the endogeneity issue due to patient–doctor relationships might not be a concern.

4.1.3 | Alternative explanation for the spillover effect of gifts

The OLS estimate of the spillover effects of gifts may also have an alternative explanation: patients may strategically time their consultations with a doctor based on whether other patients give gifts to that doctor. Existing evidence supports the idea that patients often strategically time their visits to avoid long wait times at the doctor's office (Anderson et al., 2014). In online consultation, then, when a patient observes that other patients give gifts to a doctor, he or she may infer that other patients are consulting the doctor at the moment. As such, gifts from other patients signal that a doctor is busy with consultations. Prior research also shows that doctors are less likely to provide high-quality service when they are overloaded with consultations (Weigl et al., 2016). Therefore, to receive better medical service, patients may avoid consulting a doctor when they see other patients giving gifts to that doctor.

The variable $I(otherGift)_{ijq}$ indicates whether patient i consults doctor j after other patients give gifts to doctor j. If a patient avoids consulting doctor j when he or she sees other patients giving gifts to doctor j will lower the variable $I(otherGift)_{ijq}$. As such, a negative coefficient of $I(otherGift)_{ijq}$ could be due to patients strategically postponing their consultations based on whether other patients give gifts to the doctor.

Although such strategic postponement is theoretically feasible, we argue that it is unlikely to happen in practice. This is because the platform does not directly display to visitors whether and when patients give gifts to a doctor. A patient can only obtain this information by checking other patients' consultation records individually, a time-consuming and cognitively demanding task that patients are unlikely to undertake. Despite this argument, we still run the following models to further investigate this alternative explanation:

$$\log(non\_giver_{jt} + 1) = doctor_j + time_t + \phi \cdot gift_{jt} + \varepsilon_{jt}, \tag{6}$$

$$\log(non\_giver_{jt} + 1) = doctor_j + time_t + \phi \cdot I(gift)_{jt} + \varepsilon_{jt}, \tag{7}$$

The dependent variable non_giver_{jt} is the log number of nongivers who consult doctor j after the doctor receives the first gift in hour t. If doctor j does not receive any gifts in hour t, non_giver_{jt} is the total number of patients who consult doctor j in hour t. The independent variable $gift_{jt}$ is the number of gifts doctor j receives in hour t (Equation 6). We also create a binary version of this variable, $I(gift)_{jt}$, which captures whether doctor j receives at least one gift in hour t (Equation 7). If the alternative explanation is true, the independent variable $gift_{jt}$ or $I(gift)_{jt,}$ will have a negative coefficient.[10]

It can be seen that when the calendar fixed effects are not controlled, the effects of $gift_{jt}$ (see column 1 in Table S6) and $I(gift)_{jt}$ (see column 1 in Table S7) are positive. The positive effects are likely due to clustering in patients' choice of consultation time (i.e., patients are more likely to consult a doctor at certain times). When the calendar fixed effects are added to the models, the effects of $gift_{jt}$ (see column 2 in Table S6) and $I(gift)_{jt}$ (see column 2 in Table S7) become nonsignificant. This is because the time clustering of consultation is absorbed by the calendar fixed effects.[11]

In sum, our analysis shows that patients are unlikely to time their consultations based on whether other patients give gifts to the doctor. After the calendar fixed effects are controlled for, a patient's decision whether to consult a doctor who was recently given a gift by another patient is arguably random. Therefore, we rule out this alternative explanation.

4.1.4 | Robustness analysis for the OLS estimation

A doctor's responses to patients might be partly driven by his or her past responses to the patients. To account for this possibility, we run dynamic panel models by including the first-order lagged term of the dependent variables on the right-hand side of the OLS models. We use the two-step system GMM method to estimate these dynamic panel models because the Nickell bias would be substantial given the small number of consultations per each patient–doctor pair relative to the number of patient–doctor pairs in our sample (Nickell, 1981). We use the second and longer lags of the endogenous regressors as instruments for the differenced equation and the first lag of the endogenous variables in differences as instruments for the levels equation (Roodman, 2009). A large number of instruments may cause the endogenous variables to be overfitted. Therefore, we limit the number of instruments by "collapsing" them into a single column (Roodman, 2009). This results in 20 instruments in our analysis.

This analysis shows that our results are robust to the dynamic panel specification (see Table S8). The analysis also shows that none of the first-order lagged dependent variables are significant (see Table S8). This finding is not surprising given the well-established psychological fact that humans' short-term memory is quite limited: most adults can only store about five to nine items in their short-term memory (Miller, 1956). Given the large number of consultations, it is unrealistic to expect that doctors remember their previous responses to a patient. This might explain why doctors' previous responses have no significant effects on their current responses to patients.

4.2 | Fuzzy RDD analysis

To generate converging causal evidence, we use a second empirical strategy, a fuzzy RDD, to estimate the direct and spillover effects of gifts. In doing this, we take advantage of platform updates and changes. On July 10, 2015, the platform added a gift-giving function to its mobile app for patients. Prior to that, if patients wanted to give gifts to doctors, they had to use a web browser to access the platform on their mobile phones or desktop/laptop computers. Since this update made it easier for patients to give gifts to doctors, we expect that the mobile app update increased the likelihood of patients giving gifts to doctors. It would not have any direct impact on doctors' service quality, as doctors use a different mobile app when they work on the platform, and the update was only made to the mobile app for patients.

The fuzzy RDD analysis addresses confounding factors by considering a narrow window around the mobile app update. Within this narrow window, the unobserved factors influencing doctors' service quality are likely to be similar; observations before the mobile app update, therefore, provide a comparison group for observations after the update. Our empirical strategy uses the RDD framework in a context where time is the forcing variable and treatment begins at a particular threshold in time. Such a strategy has been used in many recent studies (e.g., Pinotti, 2017).

Following the common practice of RDD (e.g., Pinotti, 2017), we restrict our analysis to the period of July 4–16, 2015, a 12-day symmetrical window around the mobile app

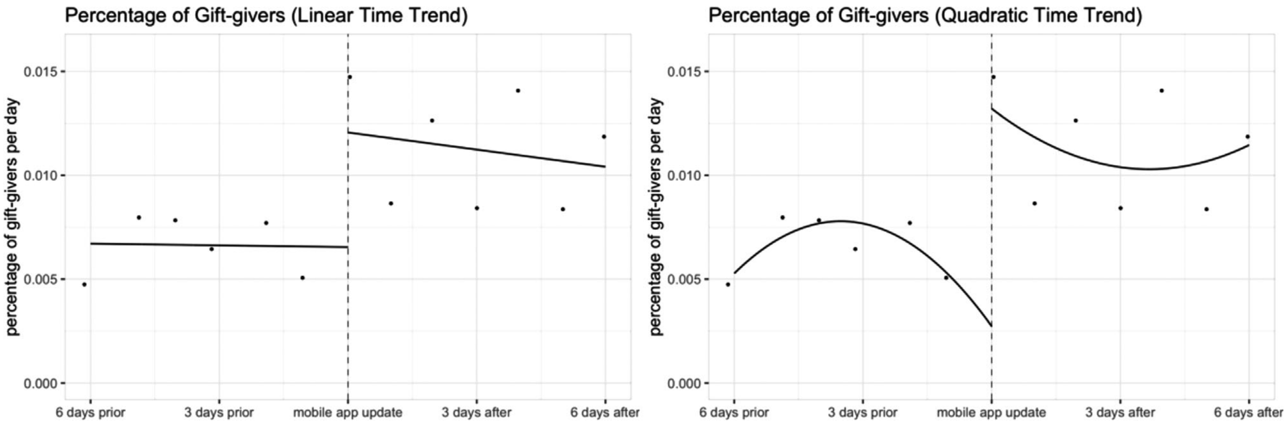

FIGURE 2 Percentage of gift-givers per day before and after the mobile app update

update, which leaves us with a total of 17,208 observations. Figure 2 shows the time trends of the percentage of gift-givers before and after the mobile app update in the sampling period. The dots in Figure 2 represent the percentage of gift-givers within 1-day bins in the 12-day period. The solid lines represent the time trends of the percentage of gift-givers based on linear and quadratic regressions, respectively. As expected, we observe an instantaneous jump in the percentage of gift-givers after the mobile app update. Similarly, Figure 3 shows the time trends of the dependent variables (i.e., patient wait time, doctors' informativeness, and emotional support) before and after the mobile app update. We observe that following the mobile app update, there is a discontinuity in each of the dependent variables in the direction that we expected, which suggests that on average doctors began to provide better service. This is graphical evidence for the direct effects of gifts from patients.

To formally estimate the effects of gifts from patients, we run the following two-stage least squares (2SLS) specification:

$$\begin{aligned} &serviceQuality_{ijq} \\ &\quad = patient\_doctor_{ij} + doctor_j + time_t + \beta_1 \cdot I(gift)_{ijq} \\ &\qquad + \beta_2 \cdot I(otherGift)_{ijq} + \sum_{k=1}^{p} \tau_k \cdot dayRelativeToUpdate_{ijq}^{k} \\ &\qquad + X_{ijq} \cdot \delta + \varepsilon_{ijq}, \end{aligned} \tag{8}$$

$$\begin{aligned} &I(gift)_{ijq} \\ &\quad = patient\_doctor_{ij} + doctor_j + time_t \\ &\qquad + \omega \cdot I(dayRelativeToUpdate_{ijq} > 0) \\ &\qquad + \beta_2 \cdot I(otherGift)_{ijq} + \sum_{k=1}^{p} \tau_k \cdot dayRelativeToUpdate_{ijq}^{k} \\ &\qquad + X_{ijq} \cdot \delta + \varepsilon_{ijq}. \end{aligned} \tag{9}$$

In these models, the variable $dayRelativeToUpdate_{ijq}$ is the date of consultation q centered at the date of mobile app update. This is the forcing variable in the RDD framework. The indicator function $I(dayRelativeToUpdate_{ijq} > 0)$ equals one if consultation q occurs after the mobile app update. The indicator variable $I(gift)_{ijq}$, representing whether patient i gives a gift to doctor j for consultation q, is an endogenous variable instrumented with $I(dayRelativeToUpdate_{ijq} > 0)$. Based on our earlier finding that patients do not strategically time their consultations based on whether others give gifts to the doctor, we treat $I(otherGift)_{ijq}$ as an exogenous variable. We run the model with a linear and a quadratic smooth function of the forcing variable $dayRelativeToUpdate_{ijq}$ (i.e., $p = 1$ and 2 in Equations 8 and 9). We do not use higher order polynomial smooth functions because a recent study shows that lower order polynomials are preferred in the local parametric approach (Gelman & Imbens, 2019).

4.2.1 | Main results from fuzzy RDD estimation

Table 5 reports results of the 2SLS with the linear and quadratic smooth functions of the forcing variable. The F-statistics of the first stage are larger than 10 (columns 7 and 8 in Table 5), suggesting that weak instrument is not a concern (Rossi, 2014). The second stage results show that gifts have a significant direct effect on patient wait time (see columns 1 and 2 in Table 5) but have no significant direct effect on doctors' informativeness (see columns 3 and 4 in Table 5). Gifts have a marginally significant direct effect on doctors' emotional support (see columns 5 and 6 in Table 5). Furthermore, gifts have a significant spillover effect on patient wait time (see columns 1 and 2 in Table 5) and informativeness (see columns 3 and 4 in Table 5), but have no significant spillover effect on doctors' emotional support (see columns 5 and 6 in Table 5). The validity of RDD depends on a few identifying assumptions, which we test in the following sections.

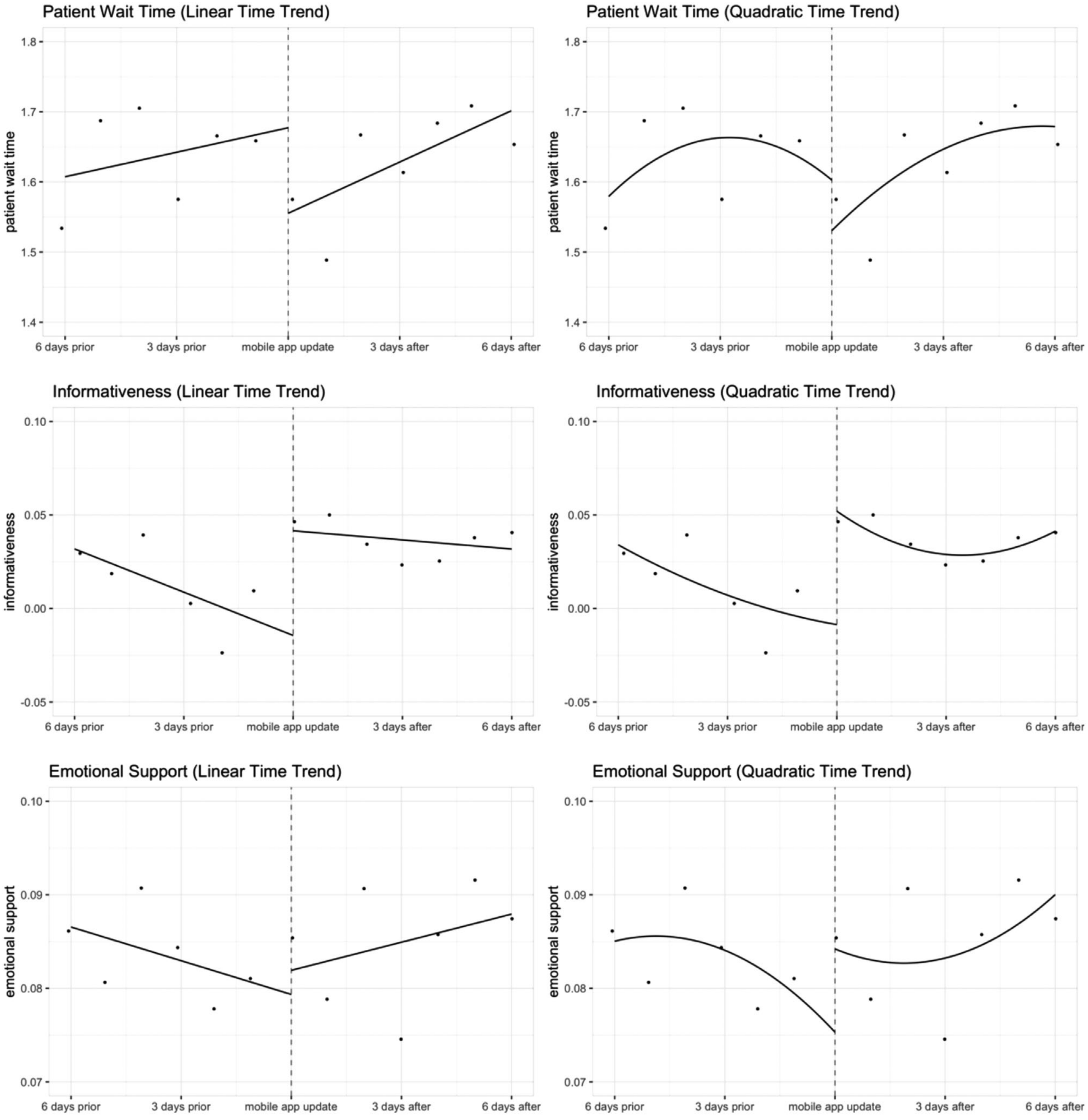

FIGURE 3 Dependent variables before and after the mobile app update

4.2.2 | Verifying the fuzzy RDD identifying assumptions

We first test whether people self-select into treatment by choosing to consult a doctor after the app update. We argue that self-selection into treatment may not be an issue because there would be no greater benefit to consulting doctors after the mobile app update. We verify this conjecture formally by plotting the distribution of patients before and after the mobile app update (see Figure S4). The dots in Figure S4 represent the average number of patients within 1-day bins in the 12-day period. The solid lines represent the time trends of the average number of patients at each side of the cutoff based on linear and quadratic regressions, respectively. We plot the 95% confidence intervals for both the linear and quadratic time trends. The overlapping confidence intervals on the two sides of the mobile app update suggest that the distribution of patients is statistically continuous at the cutoff. This confirms that patients are not more (or less) likely to consult doctors after the mobile app incorporated the gift-giving feature.

We next check whether the covariates are balanced at the cutoff. We run a series of 2SLS analyses (Equations 8 and 9) by replacing the dependent variables with the covariates.

TABLE 5 Results from fuzzy regression discontinuity design (RDD) analysis

	2SLS second stage						2SLS first stage	
	Patient wait time		Informativeness		Emotional support		I(gift)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(gift)	−11.500*	−10.900*	4.120	3.480	1.550	1.530·		
	(5.430)	(5.040)	(3.490)	(3.240)	(0.950)	(0.902)		
I(otherGift)	0.536***	0.541***	0.149*	0.144*	0.004	0.004	−0.009	−0.009
	(0.106)	(0.103)	(0.068)	(0.066)	(0.019)	(0.018)	(0.006)	(0.006)
dayRelativeToUpdate	−0.037*	−0.038**	−0.021*	−0.021*	−0.005*	−0.005*	−0.001	−0.001
	(0.015)	(0.015)	(0.010)	(0.009)	(0.003)	(0.003)	(0.001)	(0.001)
dayRelativeToUpdate^2		−0.002		0.002		0.000		−0.000
		(0.003)		(0.002)		(0.001)		(0.000)
I(dayRelativeToUpdate > 0)							0.021**	0.022**
							(0.007)	(0.007)
F-value	9.87	9.54	44.8	43	8.78	8.12	13.6	12.5
Observations	17,208	17,208	17,208	17,208	17,208	17,208	17,208	17,208

Note: (1) All controls and fixed effects are included but not reported. (2) $\cdot p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

These analyses show that there is no discontinuity in any of the covariates (see Tables S9 and S10). This is evidence that patients on both sides of the cutoff are similar to each other.

4.2.3 | Placebo and robustness tests

We further perform a placebo test by running a 2SLS analysis with an arbitrarily chosen date as the cutoff. Since this chosen date is not the real date of the mobile app update, the direct effect of gifts should not be significant. As expected, this analysis does not generate any significant direct effects (see Table S11). This further supports the validity of our RDD analysis.

We also run the RDD analysis on samples with a 10-day and a 14-day symmetrical window around the mobile app update. These samples do not generate any materially different results than when a 12-day symmetrical window is used (see Tables S12 and S13).

We further run a fuzzy RDD model that allows the slope to be different before and after the app update. Our results remain robust to this specification (see Table S14).

4.3 | Comparison of OLS and RDD analyses

There are a few differences in the OLS and RDD results. First, the direct effects of gifts from the RDD analysis are considerably larger (see Table 6). In the OLS analysis, gifts are associated with a 6.5% (i.e., $1 - e^{-0.067}$) decrease in wait time. In contrast, in the RDD analysis, gifts lead to a decrease in wait time of almost 100% (i.e., $1 - e^{-10.9}$), that is, if a patient gives a gift to a doctor, the doctor responds to that patient almost immediately. This contrast is likely due to the fact that fuzzy RDD uses 2SLS, which generates a local average treatment effect (Angrist et al., 1996). This means that the fuzzy RDD only estimates the effects of gifts in the small sample affected by the mobile app update. Figure 2 shows that the mobile app update led to an instantaneous increase in gifts, which may further generate strong effects on doctors' responses. These effects may diminish over time as doctors get used to the higher level of gifts. This may explain why the fuzzy RDD generates considerably larger direct effects of gifts than the OLS models.

Furthermore, gifts have a significant direct effect on doctors' emotional support in the OLS analysis, but the effect is only marginally significant in the RDD analysis (p-value = 0.090). This is likely due to a lack of variation in doctors' emotional support in the small RDD sample. In the RDD sample, standard deviation of $emotional_{ijq}$ is 0.332 and mean is 0.123. In 87.9% of consultations in the RDD sample, doctors did not provide any emotional support. Recall that the likelihood of doctors offering emotional support is low even in the OLS sample (see the discussion in Section 4.1). The smaller RDD sample further reduces the variation in doctors' emotional support, which makes it more difficult to detect any significant effect of gifts on doctors' emotional support.

Finally, we find that contrary to our expectation, the RDD approach generates a positive spillover effect of gifts on doctors' informativeness (the effect is also positive but not statistically significant in OLS analysis). This positive spillover effect is robust to different samples used in RDD analysis. There are two possible explanations for the positive spillover effect. First, doctors may choose to respond to the gift-givers first and only answer nongivers' questions when they are less busy with work, and doctors' answers may naturally be longer when they are less busy. Second, doctors may reciprocate to gift-givers by providing timely responses, but they may also attempt to "win over" the nongivers with longer responses.

TABLE 6 Summary of results from ordinary least squares (OLS) and regression discontinuity design (RDD) analyses

	Patient wait time		Informativeness		Emotional support	
	Direct effect	**Spillover effect**	**Direct effect**	**Spillover effect**	**Direct effect**	**Spillover effect**
OLS	-0.067^{***}	0.491^{***}	-0.029	0.018	0.090^{***}	-0.005
RDD	-10.900^{*}	0.541^{***}	3.480	0.144^{*}	$1.530^{\cdot}$	0.004

Note: The results of OLS are from the full models (i.e., columns 2, 4, and 6 in Table 2). The results of RDD are from 2SLS with quadratic smooth functions of the forcing variable (i.e., columns 2, 4, and 6 in Table 5).

To explore these possibilities, we run the following regression on the entire sample (as opposed to the smaller sample used in the fuzzy RDD approach):

$$\begin{aligned} & informativeness_{ijq} \\ & \quad = patient\_doctor_{ij} + doctor_j + time_t \\ & \qquad + \beta_1 \cdot I(gift)_{ijq} + \beta_2 \cdot I(otherGift)_{ijq} + \psi \cdot wait_{ijq} \\ & \qquad + \xi \cdot I(otherGift)_{ijq} \cdot wait_{ijq} + \sum_{m=1}^{6} \gamma_m \cdot I(gift)_{ij(q-m)} \\ & \qquad + X_{ijq} \cdot \delta + \varepsilon_{ijq}. \end{aligned} \tag{10}$$

Here, $wait_{ijq}$ is the time (in hours) between patient i's questions and doctor j's response to the questions in consultation q. The parameter of interest, ξ, captures how the spillover effect of gifts on doctors' informativeness varies with patient wait time. If the positive spillover effect is due to doctors waiting until they are less busy to respond to nongivers, we should observe that the length of responses to nongivers is greater when the wait time of these nongivers is longer; as a result, the coefficient ξ should be positive. Yet we find that as shown in Table S15, this coefficient is nonsignificant ($\xi = -0.00007$, p-value $= 0.257$). Therefore, longer responses to nongivers are not because doctors wait until they are less busy to respond to nongivers; rather, the positive spillover effect is more likely due to doctors attempting to win over nongivers by providing longer responses.

4.4 | Heterogeneity of the effects of gifts

In this section, we investigate whether the direct and spillover effects vary among different doctors (RQ3). The doctors in our sample differ in geographic location and professional experience, and the effects of gifts may vary with these characteristics. For example, high-quality medical resources in China are mostly located in the first-tier cities (e.g., Beijing). Since doctors in these first-tier cities are generally more skilled and experienced (Tu et al., 2015), they are more likely to receive gifts from patients than doctors in lower tier cities. As a result, doctors in first-tier cities may find gifts less motivating than doctors in lower tier cities. For the same reason, gifts may be less motivating for more experienced doctors than for those doctors who have less professional experience. We examine how effects of gifts vary with doctors' geographic location and professional experience by running the following model:

$$\begin{aligned} & serviceQuality_{ijq} \\ & \quad = patient\_doctor_{ij} + doctor_j + time_t + \beta_1 \cdot I(gift)_{ijq} \\ & \qquad + \beta_2 \cdot I(otherGift)_{ijq} + \eta_1 \cdot I(gift)_{ijq} \cdot moderator_j \\ & \qquad + \eta_2 \cdot I(otherGift)_{ijq} \cdot moderator_j \\ & \qquad + \sum_{m=1}^{6} \gamma_m \cdot I(gift)_{ij(q-m)} + X_{ijq} \cdot \delta + \varepsilon_{ijq}. \end{aligned} \tag{11}$$

In the above specification, $serviceQuality_{ijq}$ is the one of the three dependent variables capturing patient wait time, doctors' informativeness, and emotional support. The variable $moderator_j$ is doctor j's professional experience or whether doctor j is located in a first-tier city. To measure professional experience, we use doctors' titles, as in China and on the consultation platform, a doctor may hold one of four different titles based on their experience. Based on these titles, we categorize the doctors into two groups, one with low and one with high levels of professional experience. We then create an indicator variable $I(highRank)_j$ to capture doctors' professional experience: $I(highRank)_j$ equals one if doctor j is in the higher professional experience group. We create another indicator variable $I(firstTierCity)_j$ to capture whether doctor j is located in a first-tier Chinese city (i.e., Beijing, Shanghai, Guangzhou, or Shenzhen).

Tables S16 and S17 report how the effects of small gifts vary with doctors' professional experience and geographic location. We find that the direct effects of gifts on doctors' service quality do not vary with doctors' professional experience (see columns 1, 2, 3, 4, 5, and 6 in Table S16). However, the spillover effect of gifts on patient wait time is stronger for doctors with a higher level of professional experience (see column 2 in Table S16). In contrast, the spillover effects of gifts on doctors' informativeness and on emotional support do not vary with doctors' professional experience (see columns 4 and 6 in Table S16). Table S17 shows that neither the direct nor the spillover effects of gifts vary with doctors' geographic location.

In sum, we find that most of the direct and spillover effects of gifts from patients do not vary with doctors' professional experience or geographic location. The only exception is that the spillover effect of gifts on patient wait time is larger for doctors with greater professional experience than it is for those with less experience. This means that more experienced doctors may "discriminate" against nongivers in terms of wait time. This is likely due to the fact that when patients choose doctors for consultation, they use doctors' professional experience as a cue for quality. Indeed, Guo et al. (2017) show that professional experience is a major determinant of how much business a doctor can get on online consultation platforms, and they suggest that doctors' professional experience gives them an advantage in obtaining patients and economic returns. As such, more experienced doctors may not lose much business even if they are less responsive to nongivers.

5 | MANAGERIAL IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

Our study investigates the impact of small monetary gifts from patients on the quality (i.e., patient wait time, doctors' informativeness, and emotional support) of services provided by doctors to gift-givers (i.e., direct effect) and to nongivers (i.e., spillover effect) in the context of online medical consultation. We find that after receiving these small gifts, doctors reciprocate to the gift-givers by providing more timely responses and greater emotional support (e.g., more expressions of caring and sympathy). However, gifts from patients have no significant direct effect on doctors' informativeness.

Our findings on the direct effects of gifts are similar to those of a few prior studies (e.g., Peng et al., 2020; Wang et al., 2020). For example, these studies also find a positive link between gifts from patients and doctors' emotional support. However, there are some key differences between our study and the prior work. For example, Peng et al. (2020) and Wang et al. (2020) find a positive effect of gifts on doctors' informativeness, but this effect is not significant in our study. A possible reason is that the prior work does not control for patient–doctor relationships, a variable that might drive both patient gift-giving and doctors' service quality. This omitted variable bias may overstate the effects of gifts.

We also find that small gifts have a negative spillover effect on wait time for nongivers, that is, non-givers have to wait longer for their doctor to respond. Patient wait time is a major cause of patient dissatisfaction, but prior studies have not examined the link between gifts and patient wait time. In addition, both our OLS and RDD analyses show a positive spillover effect of gifts on doctors' informativeness, though such an effect is only significant in the RDD estimation. Our further analysis shows that the positive spillover effect is likely due to doctors providing slightly longer responses in the hope of winning over nongivers. We find no significant spillover effect of gifts on doctors' emotional support. Our analysis shows that this is likely due to a floor effect, that is, gifts may not reduce the likelihood of doctors offering emotional support to nongivers because the likelihood of doctors offering emotional support to any patient is already low.

The analysis of spillover effects of gifts further differentiates our study from prior work (e.g., Jing et al., 2019; Peng et al., 2020; Wang et al., 2020). These prior studies find positive direct effects of gifts from patients but ignore the much larger negative spillover effects. Their findings may mislead people to conclude that the gift-giving feature on online healthcare platforms prompts doctors to provide better service to patients. We further find that most of the direct and spillover effects do not vary with doctors' professional experience or geographic location, but the spillover effect on patient wait time is stronger for doctors with a higher level of professional experience. Our findings show that the effects of gifts depend on what aspect of medical service one looks at. Our study thus offers important managerial implications and opens various venues for future research.

5.1 | Managerial implications

Despite the rapid growth of online medical consultation platforms, there has been scant attention paid to the related operational issues (Bretthauer & Savin, 2018). This is a fruitful research domain, especially for researchers working at the interface of operations management and information systems (Cui et al., 2020; Khurana et al., 2019; Liang et al., 2014; Niu et al., 2019; Ru et al., 2018; Wang et al., 2018). As is the case in the offline context of healthcare operations management (e.g., Dey et al., 2013), medical service quality is an important topic in online healthcare (Kumar et al., 2018). Our study contributes to the healthcare operations management literature by examining the impact of small gifts from patients, a prevalent feature of many online medical consultation platforms, on medical service quality. While the gift-giving feature is intended to allow patients to express gratitude to doctors, our study shows that this well-meaning policy may generate unintended impacts on medical service quality. This highlights the importance of evaluating online healthcare policies based on their consequences.

Our study also has important practical implications for online medical consultation platforms. Gifts not only create positive direct effects on doctors' service quality to gift-givers, but they also create substantially larger negative spillover effects for nongivers. Therefore, when these platforms evaluate policies, it is critically important to consider the externalities of those policies.

Our results may also provide useful insight for healthcare policy makers. The Chinese government authorities have issued guidelines regarding patient gift-giving in offline settings (Zhu et al., 2018), but there is no policy addressing patient gift-giving in online healthcare. As online platforms serve a growing number of patients, governments need to respond by establishing rigorous regulations to ensure that the platforms provide fair access to high-quality healthcare. Policy makers should be cautious in regard to the prevalent practice of allowing or even encouraging patients to give small gifts to doctors on online medical consultation platforms.

We also highlight the importance of understanding the practice of patient gift-giving. Despite the small monetary value of the gifts in this context, they have significant effects on service quality. Falk (2007) compares the effects of large and small gifts in the context of charitable donation, finding that while both small and large gifts affect the frequency of donations, the effect of large gifts is 4.4 times greater than that of small gifts. Based on this finding, it stands to reason that if gifts from patients have a larger monetary value, they may have even greater effects than we observe in our study. Therefore, policy makers should pay more attention to gifts from patients regardless of their value.

Finally, our study sheds some light on the ongoing debate regarding the effects of more expensive gifts on service quality in offline settings (Zhu et al., 2018). We show that the effects of gifts differ across the dimensions of medical service quality. Therefore, one possible reason for the lack of consensus surrounding the effects of more expensive gifts in offline settings is that researchers may be looking at different dimensions of medical service quality. Medical service quality is not a monolithic concept, and our findings highlight the importance of analyzing it in its specific dimensions.

5.2 | Future research directions

This study opens up interesting opportunities for future research. First, our study only investigates gifts from patients in the context of infertility care, so our findings may not generalize to other medical specialties, especially since specialists in different fields would respond in different ways based on the severity and urgency of the conditions they treat. For example, if a patient presents with a disease that requires immediate attention (e.g., appendicitis), a small gift may not impact the immediacy of a doctor's response. Future research may examine effects of small gifts in other fields of medicine.

Second, our findings suggest that the effects of small gifts depend on the aspect of medical service under consideration. While gifts from patients have significant direct effects on patient wait time and emotional support, we do not find a significant effect on the informativeness of doctors' responses. This finding again highlights the importance of examining medical service quality as a multidimensional construct. While we contribute to the literature by considering three important dimensions of service quality that can affect patient health outcomes and satisfaction with treatment, future research may explore other dimensions of medical service quality (e.g., breadth and depth of information).

Third, our study examines gifts from patients on a platform where data on doctors' behavior are publicly available. Due to this observability of their behavior, doctors might intentionally modify their behavior to appear more ethical or socially desirable, for example, they may intentionally show that their medical services are not affected by gifts from patients (Drew et al., 1983; Tu, 2019). As a result, the observability of doctors' behavior may reduce the effects of those gifts. Even so, we still find significant direct and spillover effects. It then stands to reason that the effects of gifts would be even stronger on platforms where doctors' behavior is not visible to the public. For those platforms, our estimators provide a lower bound for the effects of gifts. Future research may investigate the degree to which observability of doctors' behavior reduces the effects of gifts.

Fourth, since we do not know the monetary value of the gifts in our sample, we can only estimate the effects of whether patients give gifts on doctors' responses. Researchers might also be interested in the effects of gift value on doctors' responses (or more precisely, the effects of one unit change in gift value on doctors' responses). One possible method to estimate the effects of gift value can be developed based on the work of MacCallum et al. (2002) who propose an equation linking the regression coefficient of a continuous variable and the regression coefficient of a binary variable dichotomizing that continuous variable. Based on this equation, researchers may perform simulations to understand the link between the effect of gift value and the effect of whether patients give gifts (see Figure S5 for an example of this simulation). Future research may also gather gift value data to more precisely estimate the effects of gift value.

Fifth, our study furthers our knowledge regarding the spillover effects of small gifts. The few prior studies of online gifts from patients to doctors focus almost exclusively on the direct effects, and the research on spillover effects generates only limited evidence for the spillover effects of symbolic gifts in a narrow context (e.g., physicians' prescription of antibiotics to patients who are socially close to a gift-giver) (Currie et al., 2013). Given the prevalence of small gifts on online consultation platforms and our finding that the spillover effects can be substantially larger than the direct effects, future research may shift focus to the spillover effects of small gifts.

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ENDNOTES

1 The Chinese government encourages hospitals to use online platforms to expand the reach of healthcare services (see http://www.gov.cn/zhengce/content/2018-04/28/content_5286645.htm for an example).

2 Doctors' working hours on the platform are flexible.

3 Patient wait time may be decomposed into two parts: the time the patient has to wait before the doctor starts studying the patient's case and the time

the doctor spends studying the case. Our data do not permit this decomposition, but we can estimate an upper bound for the time doctors spend on patient cases. Please see Section A of the Supporting Information for this estimation. It can be seen that this upper bound is extremely small. Therefore, we do not differentiate between these two components.

[4] Distinct topics are tagged by the platform. We identify distinct topics based on these tags.

[5] In the HTML code of each consultation, each question is embedded in a pair of division tags. We extract the questions from the division tags and count the number of questions in each consultation.

[6] The maximum value of m is 6 because more than 98.6% of patients have fewer than seven consultations with a doctor.

[7] β_2 can be interpreted as the effect of gifts on nongivers even though $I(otherGift)_{ijq}$ only captures whether doctor j received at least one gift from other patients. Please see a detailed explanation for the interpretation of this coefficient in Section B of the Supporting Information.

[8] We also run OLS models with the lagged terms for both $I(gift)_{ijq}$ and $I(otherGift)_{ijq}$ and with a different measure for $I(otherGift)_{ijq}$ (see Tables S2 and S3). These analyses do not change the effects of our primary interest.

[9] We also examine whether the direct or spillover effects of gifts vary between free consultation stage and paid stage. The results suggest that neither the direct nor the spillover effects of gifts vary between free consultation and paid stage (see Table S5).

[10] A direct test is to use a probit or logit model linking whether a doctor received gifts recently and whether a patient consulted that doctor. However, since we cannot observe the nongivers who decided not to consult the doctors, we can only examine whether receiving a gift impacts the number of nongivers who consult a doctor in a small time window after the gift is given.

[11] We also use 2-h and 3-h windows to run this analysis. Specifically, we examine whether a doctor receives a gift in a 2-h (or a 3-h) window affects the number of nongivers who consult the doctor after the doctor receives the first gift in the window. Similar to the 1-h window analysis, these extra analyses do not show that patients strategically postpone their consultation based on whether peer patients give gifts to the doctor (see columns 3, 4, 5, and 6 in Tables S6 and S7).

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