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THE EFFECTS OF PARTICIPATING IN A PHYSICIAN-DRIVEN ONLINE HEALTH COMMUNITY IN MANAGING CHRONIC DISEASE: EVIDENCE FROM TWO NATURAL EXPERIMENTS[1]

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This research examines physician-driven online health communities (OHC), a social media application in healthcare that engages both patients and physicians. Drawing on the "patient–physician partnership" paradigm in managing chronic disease (Bodenheimer et al. 2002), we argue that physician-driven OHC facilitates patient–physician collaborative care and self-management support, which may improve patient well-being and patient–physician relationships. We test the mutual impact between patients' and physicians' participation in physician-driven OHC and the impact of patients' and physicians' participation on patient well-being and the patient–physician relationship in the context of managing diabetes and depression. We collect data from a leading Chinese online consultation platform. To make credible causal inference, we exploit two events that separately create plausibly exogenous variations in patients' and physicians' participation. We find that physicians' participation significantly increases patients' participation for both diabetes and depression, but patients' participation only increases physicians' participation for depression. Although both patients' and physicians' participation significantly improve patient well-being and the patient–physician relationship, there are interesting nuances in these effects over time. These findings have important implications for self-managing chronic diseases and healthcare policy making.

Keywords: Physician-driven online health communities, chronic disease self-management, patient–physician relationship, patient well-being, natural experiment, instrumental variable regression, difference-in-differences

Introduction

Existing research shows that continuous communication between chronic disease patients and health professionals is a critically important factor leading to effective self-management (Sevick et al. 2007; Thorne et al. 2004). Self-management occurs mostly in nonhospital venues. As it is challenging for chronic disease patients to repeatedly consult physicians in face-to-face environments, we suggest that online health communities (OHC) that *engage both patients and physicians* can be an important means to manage chronic diseases. Such a social media application enables community-

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based care by allowing patients to continuously obtain medical knowledge and emotional support from their physicians and from peer-patients. The increasing use of OHC by patients has led to an increasing number of studies examining the effects of OHC use on the management of chronic diseases. However, existing research has mostly focused on patient-oriented OHC; that is, on OHCs where the interactions supported are between patients (e.g., PatientsLikeMe).

In contrast to existing research, our research examines physician-driven OHC (Vennik et al. 2014), a form of OHC created and maintained by physicians, in which patients can communicate with physicians with whom they have consulted on the Internet or in face-to-face environments, and also with other patients who have consulted with the same physician. A physician-driven OHC may be better suited for self-managing chronic disease than traditional patient-oriented OHCs because it enables patient–physician partnerships and generates better self-management support by integrating physicians' medical expertise and patients' experiences.

Drawing on the "patient–physician partnership" paradigm in managing chronic disease (Bodenheimer et al. 2002), we develop a conceptual framework that explains how a physician-driven OHC facilitates patient–physician collaborative care and self-management support, two components of the patient–physician partnership paradigm. We further posit that these will likely lead to improved patient well-being and patient–physician relationships. We theoretically hypothesize and empirically test the mutual impact between patients' and physicians' participation in physician-driven OHCs and the impact of patients' and physicians' participation on patient well-being and the patient–physician relationship. We investigate these in the context of managing diabetes and depression, two common chronic diseases.

We collected data from a leading Chinese online consultation platform, which allows each affiliated physician to set up his or her own OHC. After consulting with a physician on the platform, a patient can further interact with the physician and peer-patients (i.e., other patients who have consulted with the physician) in the physician's OHC. From the history of the platform, we identified two events that separately created plausibly exogenous variations in patients' and physicians' OHC participation. By exploiting these two events, we estimated the causal effects of patients' and physicians' OHC participation. Our results show that physicians' participation in their OHC significantly increases patients' participation for both diabetes and depression, but patients' participation only increases physicians' participation for depression. Although both patients' and physicians' participation in physician-driven OHCs significantly improve patient well-being and the patient–physician relationship, there are interesting nuances in these effects over time. These findings have important implications for the self-management of chronic diseases and healthcare policy making.

The paper is organized as follows. We first review related literature and develop our hypotheses. We then describe our empirical context, data collection, identification strategy, data analyses, and results. We conclude the paper by discussing the findings and their implications for the literature and healthcare practice.

Literature Review

This research contributes to a growing body of literature that investigates the use of online communities in healthcare. The existing literature has examined the effects of online communities in both the general context of healthcare and the specific context of chronic disease management.

In the general context of healthcare, existing research examines patients' motivation for using OHC and the effects of patients' OHC use on health outcomes (e.g., physical and psychological well-being). Prior research shows that patients use online health communities to meet unfulfilled informational and emotional needs from offline healthcare, including informational support (e.g., Rupert et al. 2014), emotional expression (e.g., Wentzer and Bygholm 2013), and social comparison (e.g., Malik and Coulson 2010). Both positive and negative effects of patients' OHC use have been reported in the literature. While patients' OHC use can lead to an improved physical and psychological condition (Pagoto et al. 2014; Wentzer and Bygholm 2013), it can also lead to negative outcomes, including receiving misinformation (Antheunis et al. 2013), loss of privacy (Moorhead et al. 2013), and online addiction (Malik and Coulson 2010).

In the specific context of chronic disease management, although the literature is similarly concerned with the effects of patients' OHC use on health outcomes, the existing research examines more nuanced outcomes, including patients' engagement or participation in health interventions (e.g., Schubart et al. 2011; Shigaki et al. 2008), patients' disease-specific knowledge (e.g., Schulz et al. 2009; Shigaki et al. 2008), and the social interactions between peer-patients (e.g., Rodham et al. 2009; Setoyama et al. 2011). This line of research suggests that chronic disease patients' use of OHC increases their engagement or participation in health-promoting behaviors such as seeking informational and social support (e.g., Rodham et al. 2009; Yan and Tan 2014), sharing their experiences (e.g., Rodham et al. 2009; Yan et al.

2019), and expressing their emotions (e.g., Rodham et al. 2009; Setoyama et al. 2011). The engagement further generates many benefits, including providing disease-specific knowledge (e.g., Schulz et al. 2009), facilitating communication between peer-patients and between patients and physicians (e.g., Bartlett and Coulson 2011; Oh and Lee 2012), alleviating disease-related distress (e.g., Lorig et al. 2008), and improving psychosocial and physical well-being (e.g., Lorig et al. 2008; Setoyama et al. 2011; Yan and Tan 2014). Given these positive outcomes, the literature suggests that chronic disease patients' use of OHC leads to *patient empowerment*, defined as patients' discovery and development of their inherent capacity to be responsible for their own life (e.g., Oh and Lee 2012).

In the context of chronic disease management, a large number of studies investigates the effects of patients' OHC use on the relationship between patients and health professionals with inconsistent findings. While some researchers suggest that patients' OHC use can lead to more equal relationships between the patients and healthcare professionals since OHC use reduces the information gap between patients and health professionals (e.g., Bartlett and Coulson 2011; Oh and Lee 2012), others find that patients' OHC use may impair the relationship between patients and their physicians (e.g., Broom 2005; Rupert et al. 2014; Smailhodzic et al. 2016; Wicks et al. 2010). For example, Broom (2005) argues that physicians often react negatively to health information obtained from OHC because such information increases the burden of clarification and challenges their medical authority. Physicians' negative reactions lead to suboptimal patient–physician interactions and patient dissatisfaction, which may lead to increased switching of physicians (Rupert et al. 2014; Wicks et al. 2010).

While prior research provides important insight into the use of online communities in healthcare, it has primarily focused on patients' use of OHC; less attention has been paid to how OHC can engage both patients and their physicians to achieve better health outcomes in general and in the context of chronic disease management in particular (Vennik et al. 2014). Given the long-lasting and undulating course of chronic diseases, continuous cooperation and interactions with health professionals are important (Clark 2003; Sevick et al. 2007). Considering the time and financial costs, it can be challenging for chronic disease patients to repeatedly consult physicians in face-to-face environments. Online communities that engage both patients and their physicians can be a promising solution to support continuous cooperation and interactions between patients and their physicians. Therefore, in the context of chronic disease management, it is important to extend the current literature from patient-oriented OHC (e.g., PatientsLikeMe) to OHCs that engage both patients and their physicians to understand how the joint participation by physicians and patients influences relevant outcomes. As a result, our research examines physician-driven OHCs, a form of OHC that engages both chronic disease patients and their physicians. It is also worth noting that many prior studies that have examined OHC use for chronic disease management are descriptive and/or exploratory and use research designs that limit their ability to make credible causal inference (for a discussion, see Merolli et al. 2013). Our research seeks to theoretically elaborate the effects of physician-driven OHC and empirically generate credible causal evidence by leveraging two natural experiments.

Theory Development

Definition of Variables

Our research examines patients' and physicians' participation in physician-driven OHCs and associated impacts on patient well-being and the patient–physician relationship. Before presenting our hypotheses, we first define the variables examined in the research.

The literature on online communities differentiates between active and inactive participation (Madupu and Cooley 2010; Preece et al. 2004). Active participation in an online community involves posting new messages and/or responding to others' messages. In contrast, inactive participation or lurking is merely browsing or reading messages and never posting in the community. This research focuses on active interactions between patients and physicians.

When investigating patient well-being, researchers examine either a patient's objective health status, including pain and other symptoms, disease markers (e.g., blood pressure and heart rates), and functional capacity (e.g., ability to walk), or the patient's subjective assessment of his or her health status (Larsen and Eid 2008; Ong et al. 1995; Street et al. 2009). In recent years, there has been a greater emphasis on patient-reported outcome measures (Cella et al. 2010). A subjective assessment of health can be seen as an aggregative measure reflecting a patient's overall assessment of health (Miilunpalo et al. 1997). In our research, we define patient well-being as the subjective internal state of how patients think and feel about their health status (Stewart et al. 1994).

The patient–physician relationship is defined as the way in which patients and their physicians regard and behave toward each other (Ridd et al. 2009). The most common chronic diseases are of long duration and are characterized by uncertain prognoses. Patients' and physicians' mutual familiarity with each other enables physicians to more effectively monitor the long-term development and better assist their patients in self-management (Cabana and Jee 2004). Also, patients' trust and confidence in their physicians have an important impact on compliance with and adherence to the treatment and self-management plan (Ong et al. 1995). Therefore, in the context of chronic disease, the patient–physician relationship is defined as patients' and physicians' mutual familiarity with each other, the patient's trust and confidence in the physician, and the patient's loyalty to the physician (Ridd et al. 2009).

Theoretical Framework

Our hypotheses development draws insight from Holman and Lorig (2004) and Bodenheimer et al. (2002), who emphasize the patient–physician partnership in the self-management of chronic diseases. The traditional model of healthcare delivery regards physicians and other health professionals as experts and patients as passive receivers of medical expertise. Successful self-management of chronic diseases requires a new paradigm of patient–physician partnership, in which chronic disease patients are their own principal caregivers, and physicians act as consultants supporting patients in this role (Bodenheimer et al. 2002). The patient–physician partnership paradigm regards both patients and physicians as experts: physicians are experts about the disease (i.e., the medical experts) and patients are experts about their lives (i.e., the experiential experts). Patients and physicians interact continuously, building their relationship to create better health outcomes.

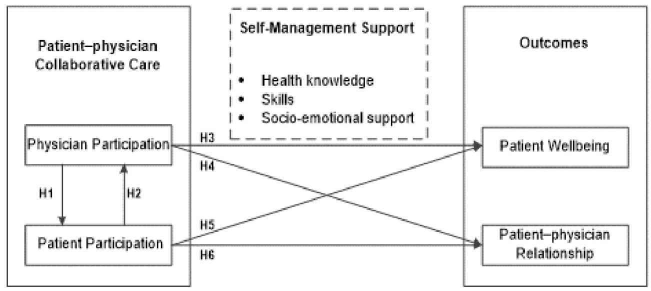
The patient–physician partnership paradigm has two components: patient–physician collaborative care and self-management education (Bodenheimer et al. 2002). We organize our hypotheses development around these two components (see Figure 1). First, we suggest that physician-driven OHC facilitates collaborative care by enabling continuous interactions between physicians and their patients, and between peer-patients. Physician-driven OHC is not simply a Q&A forum where patients ask questions and peer-patients or physicians answer them. It enables rich communicative activities including *instrumental* and *socio-emotional* communication, both between physicians and patients and between peer-patients. *Instrumental communication* is task-focused communication that aims at exchanging health and medical information with the goal of improving patients' psychological and/or physical conditions (Hall et al. 1987; Ong et al. 1995; Tates and Meeuwesen 2001). Existing research suggests that involving a health professional in social media will likely lead to greater patient participation in health interventions (Merolli et al. 2013). Therefore, physicians' instrumental and socio-emotional communication can encourage patients to seek help, share their experiences, and offer emotional support in the OHC. Conversely, patients' participation not only directly elicits physicians' responses (e.g., physicians respond to patients' posts by answering their questions or offering emotional support), but also allows the physicians to monitor information and activities for appropriateness and to address common topics in managing the disease (Lorig et al. 2008; Shigaki et al. 2008). Physician-driven OHC is a means for physicians and patients to engage each other in the management of chronic disease. The combination of physicians' medical expertise and patients' experiential knowledge will likely lead to better self-management.

Second, the original conceptualization of self-management education focuses on the development of health knowledge and skills (Bodenheimer et al. 2002). Given the psychosocial impacts of chronic diseases, we extend self-management education to self-management support, which includes the provision of health knowledge and skills, as well as socio-emotional support. Physician-driven OHC, with its ability to engage both patients and physicians and the experiential similarity of the patients, can generate more credible collective health information and more effective socio-emotional support than traditional patient-oriented online communities. We further suggest that by facilitating self-management support, physician-driven OHC will likely lead to improved patient well-being and patient–physician relationships.

Collaborative Care and the Mutual Impact of Patient and Physician Participation in Physician-Driven OHCs

The crux of collaborative care is continuous interactions between patients and physicians and the integration of physicians' medical expertise and patients' self-knowledge. It requires that patients accept responsibility for managing their own condition and solve their own problems using information from physicians (Bodenheimer et al. 2002). Physician-driven OHC facilitates collaborative care by engaging both the physician and his or her patients. We argue that there is a mutual impact between patients' and physicians' participation in physician-driven OHC.

As discussed earlier, physicians participate in OHC in different ways, including *instrumental* and *socio-emotional* communication with their patients. Instrumental communication takes the forms of voluntary information provision and responding to patients' queries. For example, our reading of physicians' posts in OHC reveals that physicians often voluntarily post general knowledge about a medical condition (e.g.,



Note: The dotted rectangle is the mediating theoretical mechanism, not tested in the current study.

Figure 1. Theoretical Framework

symptoms, diagnoses, medical tests, and treatment options), health advice (e.g., exercise, diet, a healthy lifestyle, and suggestions for alleviating acute symptoms), and cases of successful self-management. They also regularly comment on patients' self-management plans, discuss the side effects of medications, answer questions about test results, and so on. Socio-emotional communication conveys feelings and emotions; for example, physicians may post messages to encourage patients, show their concern, give reassurance, express sympathy, and so forth.

Patients also participate in OHC via instrumental and socio-emotional communication; for example, they often post questions seeking information from the physician or from peer-patients. They also voluntarily share their personal experiences of their symptoms, medications, and self-management regimen, provide information by responding to peer-patients' questions or offer emotional support to peer-patients.

Physicians' participation influences their patients' participation in several ways. First, physicians' instrumental communication, including both voluntary information provision and responding to patients' queries, will likely increase patients' motivation to participate in the OHC. Drawing on expectancy-value models, Kraut and Resnick (2011) posit that motivation to participate in an online community is a function of *expectancy* (i.e., beliefs about the probability that participation will lead to desired outcomes) and *value* (i.e., the benefits of participation) (Vroom et al. 2005). In observing that a physician actively participates in the OHC, patients become more confident that their queries will receive a response from the physician. Also, the physician's posts in the OHC allow patients to see the benefits of participating in the OHC as these posts provide disease-specific knowledge and assist patients in developing a valid understanding of the disease. Therefore, physicians' participation motivates patients to participate in the OHC by enhancing patients' expectancy of receiving physicians' responses and the perceived value of participating in the OHC.

Second, physicians' participation will likely elicit behaviors of reciprocity in the OHC, which encourage patients to participate by expressing gratitude to physicians and offering informational and/or emotional support to peer-patients. Reciprocity, including both the direct and indirect forms, is an important characteristic of online communities (Faraj and Johnson 2011). Direct reciprocity refers to a beneficiary acting in kind (e.g., expressing gratitude or returning a favor) toward his or her benefactor (Wilke and Lanzetta 1970). When a patient receives a physician's informational or emotional support in the OHC, the patient will likely act out of (direct) reciprocity to participate in the OHC by responding to the physician's messages with gratitude. Indirect or "pay it forward" reciprocity refers to a beneficiary paying the kindness forward to others who are not his or her benefactors (Wilke and Lanzetta 1970). Feelings of gratitude may elicit indirect reciprocity (Gray et al. 2014). Therefore, when a patient receives a physician's support, he or she will be more likely to participate in the OHC by extending the support to peer-patients.

H1: Physicians' participation in a physician-driven OHC has a positive impact on their patients' participation.

Patients' participation in the OHC also influences their physician's participation. While patients' motivations to participate in an OHC are well understood (e.g., Oh 2012), it is not immediately clear why physicians would participate in an OHC. Based on economic theories of prosocial behavior (e.g., Bénabou and Tirole 2006), we suggest that physicians' participation in the OHC is motivated by a combination of social reward (e.g., reputation gain), concern for self-image, and altruism.

Altruism in the medical profession is well documented in the literature (e.g., Glannon and Ross 2002). When patients ask questions in an OHC, physicians may respond because they genuinely care about their patients' health. In addition to altruism, concern for self-image may also motivate physicians to respond to patients in the OHC. Recent research on a Chinese physician-driven OHC suggests that patients often judge a physician based on the physician's participation in the OHC (Guo et al. 2017). Not responding to patients in the OHC may lead patients to judge a physician as not caring about or lacking commitment to patients. Hence, physicians may respond to patients because of self-image concerns.

Existing evidence also shows that responding to patients in an OHC is socially rewarding for physicians (Guo et al. 2017). When responding to patients in an OHC, physicians express their insights, competence, and kindness in different situations, which allows patients to see their ability, clinical experience, attitudes toward interacting with patients, and commitment to work (Guo et al. 2017). By responding to patients in an OHC, physicians strengthen relationships with patients and cultivate positive word-of-mouth, which may ultimately benefit them by retaining existing patients and obtaining new patients. Therefore, such social reward may motivate physicians to respond to patients in an OHC.

Finally, the asynchronous nature of the communication facilitates physicians' participation in an OHC. Although many physicians may be overloaded at work, the asynchronous communication of OHC allows physicians the time and space freedom to respond to patients. Therefore, we posit the following:

H2: Patients' participation in a physician-driven OHC has a positive impact on physicians' participation.

Patients' and Physicians' Participation, Self-Management Support, Patient Well-Being, and the Patient–Physician Relationship

Patients self-manage chronic disease more effectively if they obtain sufficient knowledge (e.g., knowledge about the diagnosis and its implications, available treatments, and consequences), develop necessary skills to cope with symptoms (e.g., pain, fatigue, and disability), carry out health behaviors (e.g., exercise, diet, and relaxation), and obtain socio-emotional support to maintain adequate psychosocial functioning (Ryan and Sawin 2009). Next, we argue that physicians' and patients' participation in physician-driven OHC generates self-management support by increasing health knowledge, skills, and socio-emotional support, thus further improving physicians' relationships with their patients and their patients' well-being.

The Impact of Physicians' Participation on Patient Well-Being and the Patient–Physician Relationship

Information provided by physicians in their OHC will likely help patients improve their health knowledge and skills. At the onset of chronic disease, inexperienced patients may feel vulnerable and helpless in the face of the complexity of the disease. It may be difficult to independently develop a clear understanding of their diagnosis and treatment (e.g., interpreting test results and knowing treatment options and their consequences). These "uninitiated" patients may even experience difficulty in asking the "right" questions. Physicians can positively assist patients at this stage by voluntarily providing information about the causes, common symptoms, complications, tests and diagnoses, treatments and medications, as well as their potential impacts on the patients' future. These messages, often posted as "sticky threads" (i.e., messages that permanently stay at the top of an online forum), not only assist patients in developing a general understanding of their disease, but also psychologically prepare them for long-term management. Patients with chronic diseases typically need to adjust their medications, treatment plans, and daily activities from time to time. Therefore, for more experienced patients, physicians can also utilize their OHC to help these patients adapt their self-management regimens to their current conditions.

Effective chronic disease self-management requires certain skills. For example, patients need the skills to carry out exercise and healthy eating plans, and use various medical tools to monitor symptoms (e.g., plasma glucose, blood pressure, and heart rate). Physicians can either directly provide information about these skills in their OHC or direct patients to credible sources where patients can learn these skills themselves.

Many prevalent chronic diseases (e.g., diabetes and depression) have important psychosocial consequences. The presence of physical symptoms, such as pain and fatigue, combined with the need for disease management regimes, are likely to interfere with many aspects of daily life. Many chronic disease patients regularly struggle with feelings of isolation, sadness, and anger. Uncertainties regarding further complications of the disease also lead to anxiety and fear. In an OHC, physicians can express sympathy, compassion, and reassurance. These emotionally supportive messages may help reduce the psychological distress and harmful physiological arousal caused by the disease. They also provide patients with hope, confidence, and a positive attitude toward their condition, which may motivate them to actively manage the condition (Clark et al. 1991).

In essence, the above arguments suggest that physicians' participation in their OHC empowers patients by delivering useful clinical and socio-emotional information. In contrast to the empowerment enabled by conventional patient-oriented OHC (e.g., PatientsLikeMe), physician-driven OHC provides scientifically supported and evidence-based information as opposed to purely experiential and anecdotal information, mitigating the harmful effects of misinformation (Merolli et al. 2013) and leading to improved patient well-being (Norris et al. 2002; Siminerio 2010). Therefore, we posit the following:

H3: Physicians' participation in a physician-driven OHC has a positive impact on their patients' well-being.

When physicians voluntarily provide health knowledge in their OHC, they demonstrate not only their medical expertise but also benevolence. Similarly, by responding to patients' questions, physicians not only provide useful health information, but also alleviate their patients' anxiety stemming from the uncertainties surrounding their situation (Street et al. 2009). Because of the OHC, patients do not have to wait until the next appointment to obtain answers to simple questions. By participating in their OHC, physicians show that they will "be there" for the patients in their time of need. Therefore, physicians' participation in their OHC will likely increase their patients' trust and confidence in their medical expertise and benevolence. We thus posit the following:

H4: Physicians' participation in a physician-driven OHC has a positive impact on the relationship between patients and their physician.

The Impact of Patients' Participation on Patient Well-Being and the Patient–Physician Relationship

Patients' participation in physician-driven OHC can also help chronic disease patients obtain health knowledge, skills, and socio-emotional support. The participation of patients enables the "wisdom of the crowd." While some patients' questions in a physician's OHC may be overlooked by the physician, they can typically receive timely responses from knowledgeable or experienced peer-patients. In addition to the wisdom of the crowd effect, information from peer-patients has the following unique benefits.

First, while information provided by physicians is typically evidence-based and supported by scientific research, information from peer-patients is experiential and anecdotal (Allen et al. 2016). Despite its anecdotal nature, information from peer-patients plays an important role because it addresses chronic disease patients' desire to obtain as much information and as many perspectives as possible, to ensure nothing important is missing (Allen et al. 2016). Further, a defining characteristic of the physician-driven OHC is that patients in the community are not only managing the same disease, they have also consulted with or been treated by the same physician. The experiential similarity makes the information provided by peer-patients in a physician-driven OHC more relevant and credible than information from other social media sources (Gage-Bouchard et al. 2017).

Second, information provided by physicians can be generic, abstract, and lacking in concrete examples to help comprehension (Castro et al. 2007). In contrast, information from peer-patients normally contains rich personal and contextual details, such as the demographic background and medical history of the information provider (Malik and Coulson 2011). These personal and contextual details allow peer-patients to see more concretely the progression of symptoms, future complications, and different ways to cope with these issues. Personal and contextual details also enable social comparison, through which peer-patients can assess the appropriateness of their own information, beliefs, and behaviors (e.g., using tobacco or alcohol, attending to diet, seeking preventive care, and complying with medical regimens).

Third, while physicians' socio-emotional support is primarily based on sympathy, peer-patients' socio-emotional support is based on empathy as well as sympathy. Physicians do not necessarily have firsthand experiences of their patients' situations. In contrast, because of the experiential similarity, peer-patients in physician-driven OHCs have an in-depth understanding of the many dimensions and nuances of the disease. They are able to take on the role of their peers and understand their emotional reactions and practical concerns (Escalas and Stern 2003). This is the essence of empathy. Socio-emotional support based on empathetic understanding enables patients to vent their feelings without worrying about being denied, dismissed, or criticized. Having "been there" themselves, peer-patients tolerate expressions of frustration and validate the normalcy of the person's psychological reactions (Thoits 2011). Further, socio-emotional support from peer-patients may reduce chronic disease patients' feelings of isolation more effectively than support from other sources. The persistent symptoms of chronic disease may disrupt the patients' social and professional life. Patients likely feel out of touch with their family, friends, and colleagues. Socio-emotional support from "similar others" may alleviate the feeling of isolation and bolster weakened self-worth (Thoits 2011). Because of these benefits, we suggest that patients' participation in physician-driven OHC can also improve patient well-being.

H5: Patients' participation in a physician-driven OHC has a positive impact on patients' well-being.

A patient receives greater informational and socio-emotional benefits when his or her peer-patients actively participate in the OHC. When patients benefit from peers' participation, they feel grateful not only toward their peer-patients but also the physician, because it is the physician who sets up the OHC and brings together patients. Patients may make inferences about the physician's competence, benevolence, and personality in general based on the level of peer-patient participation in the OHC. For example, when seeing a low level of patient participation, a patient may infer that "not many patients choose to consult with the physician" and "the physician is probably not competent." In contrast, when seeing a high level of patient participation, a patient might infer that "since the physician makes a great effort to encourage patients' participation in the OHC, the physician must have patients' best interests at heart" or "the physician must be a warm and friendly person because his or her patients are willing to share their thoughts."[2] Positive inferences about a physician's traits will likely lead to patients' positive emotional and behavioral reactions toward the physician (Fiske et al. 2007). Therefore, we posit the following:

H6: Patients' participation in a physician-driven OHC has a positive impact on the relationship between patients and the physician.

Empirical Analysis and Hypotheses Testing

Empirical Context

We collected data from a Chinese online medical consultation platform. The platform was founded in 2006, and provides online consultations for patients across the country. As of July 2017, about 154,640 physicians had registered with the platform. The platform maintains a homepage for each registered physician, containing the physician's professional and biographic information. Patients can browse the physicians' information and consult with the physicians at their hospitals or via mobile phone or the Internet platform. For Internet-based consultations, patients and physicians directly communicate on the platform. For mobile phone-based consultations, patients call physicians through the web or the mobile app of the platform. To see a participating physician offline, patients are required to make an appointment with the physician on the platform.

A patient's first three online consultations with a physician are free of charge. After the free consultations, the patient pays a consultation fee for each new consultation if he or she continues to consult with the same physician. The patient can also switch to a different physician, in which case the patient will have another three free consultations with this new physician. The platform uses a revenue sharing model, whereby 70% of its revenue is distributed to the participating physicians.

For each physician, a summary record of all consultations is publicly available on the physician's homepage, which shows when each patient consulted with the physician. To protect patient privacy, the summary record does not show patients' personal identity information (e.g., name and account ID). Each patient is identified with a string of numbers in the summary record.[3] Further, patients are regularly invited by the platform to post comments on their health status on the homepage of the physician. Patients can also rate their satisfaction with the physician. The summary record, patients' comments on their health status, and patients' satisfaction ratings are visible to visitors of the platform.

This research examines physician-driven OHC, an important feature of the platform. The platform allows every registered physician to set up his or her own OHC. Setting up an OHC is optional, but if a physician chooses to use the OHC function, patients who have consulted with the physician are automatically granted membership to the physician's OHC. After obtaining membership, patients can interact with the physician and peer-patients (i.e., other patients who have consulted with the physician on the platform) in the physician's OHC.

Interactions with a physician in the physician's OHC and *consultations* with the physician are two distinct activities on the platform. While a consultation is a paid service that involves a formal one-to-one communication between a patient and a physician, interactions with a physician in the OHC is free of charge once membership to the OHC is granted to the patient. Further, while in the consultations, physicians are obligated to answer patients' questions, they have no obligation to answer patients' posted questions or participate in the OHC. In fact, among physicians who have set up an OHC, there is a large variation in the degree to which they participate. While some frequently communicate with their patients in their OHC, others rarely participate. Our research focuses on the activities in the OHC (i.e., on physician interactions on the OHC and not their consultations), but we also use information about the consultations to operationalize some of our variables.

[2]The specific examples provided here have been derived from informal interviews with patients of this online community.

[3]The string of numbers is not the patient's account ID on the consultation platform.

To protect patient privacy, the platform provides guidelines for interactions between patients and physicians in the OHC. While exchanges of generic health and medical information are allowed between patients and physicians, the guidelines discourage patients from asking physicians questions that contain details of personal conditions and other private information. The platform also discourages physicians from answering patients' questions that require discussions or assessments of their personal conditions. Although patient posts are visible to all members of the OHC, the OHC does not display any patient identity information; thus patient posts are anonymous.

Empirical Strategy

This research examines the mutual impact between patients' and physicians' participation in physicians' OHC and the impact of patients' and physicians' participation on patient well-being and on the patient–physician relationship. The challenge to credible causal inference is that the observed associations between these variables are confounded by alternative explanations. For example, we hypothesized a bidirectional causal effect between patients' and physicians' OHC participation. However, the observed association between patients' and physicians' participation may be solely driven by a unidirectional causal effect (e.g., only a physician's participation may have a causal effect on patients' participation). Further, any observed association between patients' or physicians' OHC participation and patient well-being or the patient–physician relationship may not necessarily be due to the causal effects we hypothesized. For example, when a physician has good relationships with his or her patients, patients would be more likely to participate in the physician's OHC. In this case, the direction of the causality is opposite to what we hypothesized.

To generate credible causal evidence for our hypotheses, we exploit two events that create plausibly exogenous variations in patients' and physician's OHC participation respectively. On May 22, 2012, the platform launched a mobile app for patients. The mobile app was released in the forms of both a native app, which patients can download from the app store and install on their mobile device, and a mobile-optimized website, to which patients are automatically directed when they access the platform on a mobile device without the native app. The mobile-optimized website and the native app have identical interfaces. They have all the functions of the desktop version of the platform (e.g., searching for, making appointments with, and consulting with physicians) but do not provide access to physicians' OHCs. To use the OHC on a mobile device, patients have to scroll to the bottom of the mobile site, where they are given the option to switch to the desktop version of the platform on their mobile device. We expect that introducing the mobile app reduced patients' participation in OHCs. Before the launch of the mobile app, patients used the desktop version of the platform on both PCs and mobile devices, which allowed them to easily access the OHC. The mobile app requires an extra effort for patients to use the OHC on the mobile channel: they need to scroll to the bottom of the site and switch to the desktop version. Also, patients may not immediately know that they have the option of using the OHC on their mobile phone by switching to the desktop version. Given this is a mobile app only for patients, it should affect patients' participation directly, and ultimately affect physicians' participation only through patients' participation. Therefore, the launch of the mobile app generates a natural experiment in which patients' participation in physicians' OHCs was reduced exogenously. We exploit the natural experiment to identify the causal effects of patients' participation in physicians' OHCs.

The second event is an announcement directed to physicians on July 1, 2014. The platform regularly sends messages containing guidelines, suggestions, or policy updates to participating physicians. This particular message started with words of gratitude to the participating physicians for choosing the platform. It then explained the intent of the OHC (i.e., to help physicians better connect with patients to create positive word-of-mouth) and encouraged physicians to use the OHC. The message had a reminding effect. It prompted physicians to participate in the OHC by making the benefits of participation more salient (i.e., better connection with patients and positive word-of-mouth). Also, the announcement was delivered to physicians in the form of a "strategic message," which carries a sense of importance. As a result, physicians are more likely to follow the message's suggestions. The announcement is only visible to physicians, not patients. Therefore, the announcement creates another natural experiment in which physicians' participation in their OHC was increased exogenously. We use this event to identity the causal effects of physicians' participation in the OHC.

Data Collection

Although data about many different medical conditions are available from the platform, we restrict our analysis to diabetes and depression. Both of these are common chronic diseases, but they have an important difference: while diabetes is primarily a physical illness, depression is primarily a psychiatric disorder. Looking at two different types of chronic diseases serves to increase the generalizability of our findings.

We collected two waves of data from the platform, which capture the two natural experiments, respectively. The first wave contains monthly data from February 22, 2012, to

August 22, 2012; that is, two 3-month periods before and after the launch of the mobile app. The second wave of data contains monthly data from April 1, 2014, to September 1, 2014; that is, two 3-month periods before and after the announcement that encouraged physicians to participate in their OHC. The two chronic diseases (i.e., diabetes and depression) and the two natural experiments lead to four datasets used in the analysis, which we labeled "diabetes2012," "diabetes2014," "depression2012," and "depression2014." The four datasets contain all physicians specializing in diabetes or depression, including both those who set up an OHC and those who did not. All four datasets contain the following data gathered from each physician's homepage: the physician's geographic location, the physician's title,[4] the physician's affiliated hospital, patient-generated rating of their satisfaction with the physician, the physician's consultation records, each of his or her patients' self-reported health status, and the physician's and his or her patients' posts in the OHC (if he or she set up an OHC).

Variables and Descriptive Statistics

Our unit of analysis is each physician's OHC. Patients' and physicians' participation are operationalized based on patients' and physicians' posts in this OHC. We denote physicians' participation as $physician\_post_{it}$, which is the number of physician i's posts in his or her OHC in month t. We denote patients' participation as $patient\_post_{it}$, which is the number of patients' posts in physician i's OHC in month t.

We measured the patient–physician relationship based on the suggestion that a good patient–physician relationship is revealed as patient preference for seeing the physician repeatedly over time (Ridd et al. 2009). As mentioned earlier, a patient's first three consultations with a physician are free of charge on the platform. The patient can switch to a different physician for another three free consultations. However, if the patient does not switch and chooses to pay the physician for further consultations, this is an indication of a good patient–physician relationship. The more patients who have consulted a physician more than three times, the more likely it is that the physician has a good relationship with his or her patients. We denote the variable as $relationship_{it}$, which is calculated as the percentage of patients who consulted physician i in month t and had consulted physician i more than three times by the end of month t compared with all patients who consulted physician i in month t. Patients' well-being is operationalized based on patients' self-reports of health status improvement on each physician's homepage. Specifically, we denote this variable $well\text{-}being_{it}$, which is calculated as the percentage of patients who reported a health status improvement on physician i's homepage in month t compared with all patients who reported their health status in month t.[5]

We also used several physician-level variables as controls, including the physician's title (denoted as $title_i$, which takes the value one for chief physician, and zero for physicians with lower-ranked titles), the physician's hospital rank (denoted as $level_i$, which takes the value one for the highest-ranked hospitals, and zero for lower-ranked hospitals),[6] the GDP of the city where the physician is located (denoted as $gdp2012_i$ and $gdp2014_i$), the patient-generated rating of their satisfaction with the physician at the end of month t (denoted as $reputation_{it}$), and the total number of patients that had consulted the physician by the end of month t ($totalpatients_{it}$). The variables used in our analysis are summarized in Table 1. Their means and standard deviations are reported in Table 2. More detailed month-by-month statistics are available in Appendix A.

We further verified whether the two events led to changes in patients' or physicians' participation in physicians' OHCs, as expected. We calculated the average number of patients' posts over different lengths of time (i.e., one-month, two-month, and three-month periods, respectively) before and after the launch of the mobile app (see Table 3). Paired T-tests show the launch of the mobile app significantly reduced patients' posts, as expected. We similarly calculated the average number of physicians' posts in their OHC over different lengths of time before and after the announcement that encouraged physicians' OHC participation (see Table 3). Paired T-tests support that the announcement significantly increased physicians' participation.

Data Analysis

To test our hypotheses, we ran different analyses using different subsets of data we collected. We first ran instrumental variable (IV) regressions to analyze the mutual impact of patients' and physicians' OHC participation (i.e., H1 and H2). Since the dependent variables in this analysis are patients' and physicians' OHC participation, we naturally only looked at the physicians who had set up an OHC. The IV regressions estimate causal effects by exploiting the part of variation driven by the two natural experiments.

[4]In China, every physician has a title (e.g., "chief physician"), primarily based on their professional experience.

[5]In our sample, about 27% of patients self-reported their health status.

[6]Operationalizing physicians' title and hospital rank as categorical variables with multiple values does not materially change the results.

Table 1. Variables and Measures		
Variable	**Measure**	**Data Source**
$relationship_{it}$	The percentage of patients who consulted physician *i* in month *t* and had consulted physician *i* more than three times by the end of month *t* compared with all patients who consulted physician *i* in month *t*	Summary record of consultations from physician *i*'s homepage
$wellbeing_{it}$	The percentage of patients who reported a health status improvement on physician *i*'s homepage in month *t* compared with all patients who reported their health status in month *t*	Patients' self-reports from physician *i*'s homepage
$patient\_post_{it}$	The number of patient posts in physician *i*'s OHC in month *t*	Physician *i*'s OHC
$physician\_post_{it}$	The number of physician *i*'s posts in his or her OHC in month *t*	Physician *i*'s OHC
$reputation_{it}$	The patient-generated rating of their satisfaction with the physician at the end of month *t*	Patient-generated rating from physician *i*'s homepage
$totalpatients_{it}$	The total number of patients that had consulted the physician by the end of month *t*	Summary record of consultations from physician *i*'s homepage
$gdp2012_{i}$	GDP of physician *i*'s city in 2012	China Statistical Yearbook
$gdp2014_{i}$	GDP of physician *i*'s city in 2014	China Statistical Yearbook
$title_{i}$	Physician *i*'s title, which takes the value one for "chief physician," and zero for physicians with lower-ranked titles	Physician *i*'s homepage
$level_{i}$	Physician *i*'s hospital rank, which takes the value one for the highest-ranked hospitals, and zero for lower-ranked hospitals	Physician *i*'s homepage

Table 2. Variables and Their Means and Standard Deviations				
Variable	**diabetes2012**	**diabetes2014**	**depression2012**	**depression2014**
$relationship_{it}$	.072 (.209)	.031 (.135)	.080 (.200)	.056 (.176)
$wellbeing_{it}$	.093 (.284)	.066 (.247)	.131 (.331)	.104 (.303)
$patient\_post_{it}$	1.919 (37.695)	.090 (1.678)	3.544 (44.195)	.213 (2.122)
$physician\_post_{it}$	.095 (1.377)	.028 (0.271)	.125 (1.004)	.107 (1.116)
$reputation_{it}$	.576 (.467)	.631 (.451)	.642 (.429)	.665 (.414)
$totalpatients_{it}$	168.374 (572.200)	228.481 (805.380)	319.071 (806.149)	468.561 (1250.764)
$gdp2012_{i}$	7673.69 (6078.463)		9590.522 (6158.272)	
$gdp2014_{i}$		9235.998 (7124.63)		11310.05 (7092.769)
$title_{i}$	.558 (.497)	.521 (.500)	.507 (.500)	.475 (.500)
$level_{i}$	.844 (.363)	.835 (.372)	.828 (.377)	.820 (.384)
No. of physicians	933	1183	736	904

Note: Cells contain mean values and standard deviations (in parentheses).

Table 3. Patients' and Physicians' Posts Before and After Events

	One-month pre-treatment period	*One-month post-treatment period*	*Paired T-test*	*Two-month pre-treatment period*	*Two-month post-treatment period*	*Paired T-test*	*Three-month pre-treatment period*	*Three-month post-treatment period*	*Paired T-test*	*No. of physician-driven OHC*
Patients' posts	10.75	7.78	T = 3.182, p = .002	19.57	13.11	T = 3.485, p = .001	28.36	18.64	T = 4.305, p = .000	562
Physicians' posts	.04	.14	T = -2.256, p = .024	.14	.46	T = -2.811, p = .005	.22	.79	T = -3.789, p = .000	755

We then ran difference-in-differences (DD) models to analyze the effects of patients' and physicians' OHC participation on patient well-being and the patient–physician relationship. The DD analysis was used because the outcome variables (i.e., patient well-being and patient–physician relationship) can be measured for both physicians who had set up an OHC and those who had not set up an OHC. Physicians who had set up an OHC are the "treatment group" and physicians who had not set up an OHC are the "control group," based on the fact that the two treatment events only affected the physicians who had set up an OHC.

Estimating the Mutual Impact between Patients' and Physicians' Participation in the OHC: Instrumental Variable Regressions

We ran two IV regressions to analyze the two natural experiments separately. The first IV regression used the dataset for the natural experiment that exogenously reduced patients' OHC participation (i.e., the release of the mobile app for patients) to assess the effect of patients' OHC participation on their physician's OHC participation. Formally, we ran the following regression:

$$physician\_post_{it}=\alpha_i+\beta*patient\_post_{it} + \gamma_1*reputation_{it} + \gamma_2*totalpatients_{it} + \varepsilon_{it} \quad (1)$$

where $physician\_post_{it}$ is the log of the number of physician i's posts in his or her OHC in month t and $patient\_post_{it}$ is the log of the number of patient posts in physician i's OHC in month t. We controlled for physician fixed effects (α_i), patient-generated ratings of their satisfaction with physician i at the end of month t ($reputation_{it}$), and the total number of patients who had seen physician i by the end of month t ($totalpatients_{it}$). We instrumented $patient\_post_{it}$ with a dummy variable d_{1t} indicating whether month t was after the event that exogenously reduced patients' participation in the OHC.

Table 4 reports the results of the OLS and IV regressions (with two stages) for both diabetes and depression. The OLS estimate of the effect of patients' OHC participation on their physicians' OHC participation is significant for both diabetes and depression (columns 1 and 7 in Table 4). Since the OLS estimate does not have a causal interpretation, we focus on the IV regression in the discussion of results. The first stage of the IV regression is highly significant, as indicated by the F-statistics for the event dummy (columns 2 and 8 in Table 4), which mitigates the weak instrument concerns (Rossi 2014). The second stage of the IV regression shows that patients' participation in the OHC has a significant impact on physicians' participation for depression (column 9 in Table 4) but not for diabetes (column 3 in Table 4).

The second IV regression used the dataset containing the natural experiment that exogenously increased physicians' participation in their OHC (i.e., the announcement encouraging physicians' participation) to assess the effect of physicians' OHC participation on patients' OHC participation:

$$patient\_post_{it} = \alpha_i + \beta*physician\_post_{it} + \gamma_1*reputation_{it} + \gamma_2*totalpatients_{it} + \varepsilon_{it} \quad (2)$$

where $patient\_post_{it}$ is the log of the number of patient posts in physician i's OHC in month t and $physician\_post_{it}$ denotes the log of the number of physician i's posts in his or her OHC in month t. As in the first IV regression, we controlled for physician fixed effects (α_i), patient-generated ratings of their satisfaction with physician i at the end of month t ($reputation_{it}$), and the total number of patients who had seen physician i by the end of month t ($totalpatients_{it}$). We instrumented $physician\_post_{it}$ with a dummy variable d_{2t} indicating whether month t was after the event that exogenously increased physicians' participation in the OHC.

The OLS regression shows a significant effect of physicians' OHC participation on patients' OHC participation for both diabetes and depression (columns 4 and 10 in Table 4), but OLS consistently underestimates these effects compared with IV regressions. The first stage of the IV regression again shows that weak instrument is not a serious concern, as indicated by the large F-statistics (columns 5 and 11 in Table 4).

Table 4. Instrumental Variable Regressions

Disease	Diabetes						Depression					
Dependent Variable	Physicians' Post			Patients' Post			Physicians' Post			Patients' Post		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Type of regression	OLS	IV 1st Stage	IV 2nd Stage	OLS	IV 1st Stage	IV 2nd Stage	OLS	IV 1st Stage	IV 2nd Stage	OLS	IV 1st Stage	IV 2nd Stage
Patients' post	.130*** (.024)		.141 (.183)				.077*** (.024)		.270*** (.074)			
Physicians' post				.127* (.053)		.375* (.156)				.158*** (.039)		.263* (.124)
Event 1 dummy (d_{1t})		-.102*** (.026)						-.213*** (.031)				
Event 2 dummy (d_{2t})					.057*** (.011)						.103*** (.017)	
Physicians' reputation	.158 (.114)	.019 (.215)	.159 (.115)	-.064* (.026)	.160* (.079)	-.103* (.044)	.281 (.147)	.198 (.167)	.247 (.148)	-.006 (.079)	-.050 (.069)	-.001 (.079)
Total # of patients	-.048 (.048)	-.013 (.068)	-.047 (.057)	.046*** (.013)	-.017 (.057)	.038* (.016)	-.018 (.044)	.108 (.060)	.003 (.041)	.076 (.046)	.026 (.060)	.062 (.048)
F-value on event dummy		15.19***			28.34***			48.09***			38.32***	
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust clustered error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	262	262	262	360	360	360	300	300	300	395	395	395
R-Squared	.542	.797	.522	.767	.314	.763	.526	.815	.521	.711	.342	.702

Note: **p < 0.001; **p < 0.01; *p < 0.05

The second stage of the IV regression shows that physicians' participation in their OHC has a significant impact on patient participation for both diabetes (column 6 in Table 4) and depression (column 12 in Table 4).

Additional Analyses for the Instrumental Variable Approach

The instruments used in our analyses are binary variables indicating whether the treatment events occurred in a given month. Such instruments preclude us from controlling for time trends in the dependent variables using month fixed effects because the instruments are collinear with the month fixed effects. Not controlling for month fixed effects poses a potential threat to the causal interpretation of our findings. For example, a decrease in physicians' OHC participation could simply be due to a decreasing time trend in the sampling period rather than due to a decrease in patients' participation in the OHC. Similarly, an increase in patients' participation could simply be due to an increasing time trend rather than due to their physician's participation. While there are no strong *a priori* reasons to believe that there are systematic time trends in the dependent variables in the sampling periods, we nevertheless run the following analyses to further rule out the possibility that the findings are simply due to time trends.

First, we run the OLS with month fixed effects on equations 1 and 2. If the changes in the dependent variables were solely due to time trends, adding month fixed effects to the OLS would render the independent variable of interest (i.e., patients' or physicians' participation in the OHC) nonsignificant. The results show that these independent variables remain significant after including month fixed effects in the OLS (see Table 5).

Second, to control for time trends in the IV analysis, we use alternative instruments that are not collinear with month fixed effects. These alternative instruments were identified based on the logic of Arellano and Bover (1995) and Blundell and Bond (1998). Specifically, we jointly estimated a level equa-

Table 5. OLS with Month Fixed Effects

	Diabetes		Depression	
Dependent Variable	***Physicians' Post***	***Patients' Post***	***Physicians' Post***	***Patients' Post***
Column	**(1)**	**(2)**	**(3)**	**(4)**
Patients' post	.130*** (.024)		.068** (.024)	
Physicians' post		.123* (.053)		.151*** (.039)
Physicians' reputation	.154 (.112)	-.059* (.027)	.281* (.133)	-.011 (.076)
Total # of patients	-.055 (.059)	.035*** (.010)	.040 (.043)	.051 (.043)
Time FE	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Robust clustered error	Yes	Yes	Yes	Yes
No. of physicians	262	360	300	395
R-Squared	.543	.768	.530	.712

Note: The p-values read as follow: *p < 0.05; **p < 0.01; ***p < 0.001

tion and a differenced equation for both equations 1 and 2. We used the second lag of the endogenous variables as instruments for the transformed equation and the first lag of the endogenous variables in differences as instruments for the levels equation (Roodman 2006). Again, the results show that adding month fixed effects after using the alternative instruments does not materially change the results (see Table 6). These additional analyses rule out the possibility that our findings are simply due to time trends of the dependent variables. The analysis using alternative instruments has the additional benefit of probing treatment effect heterogeneity (Angrist 2004). The IV approach identifies a "local average treatment effect," that is, a causal effect only for the subpopulation affected by the treatment (Angrist and Imbens 1995). Clearly, not all physicians are equally affected by the two treatment events. Using the alternative instruments (which are not from the treatment events) shows that our findings from the IV analyses have credible causal interpretations beyond the subpopulation affected by the treatment events.

Estimating the Impact of Patients' and Physicians' Participation on Patient Well-Being and the Patient–Physician Relationship: Difference-in-Differences Analysis

Before running the DD analysis, we used propensity score matching (PSM) to select the treatment (i.e., physicians who had set up an OHC) and control (i.e., physicians who had not set up an OHC) groups that are comparable on physician-level variables so that the differences in outcomes (i.e., patient well-being and patient–physician relationship) cannot be attributed to the differences in the physician-level variables.

Propensity Score Matching: We first estimated the propensity scores using a logit model based on physician-level variables including the physician's title, the physician's hospital rank, the GDP of the city where the physician is located, the patient-generated rating of their satisfaction with the physician, and the total number of patients that had consulted with the physician. We then matched the physicians in the treatment and control groups using the Kernel-based method (Heckman et al. 1997, 1998). For a given physician in the treatment group, the method creates a match by taking a weighted average of multiple physicians in the control group. The Kernel-based method was chosen because it takes more information from those who are closer matches and down weights more distal observations (Caliendo and Kopeinig 2008; Guo and Fraser 2014).[7] We compared the physician-level matching variables between treatment and control groups before and after matching to see if the two groups were balanced on these variables (see Table 7). It can be seen that after matching, the treatment and control groups have no significant differences on these variables.

[7]We also performed one-to-one matching, which created less balanced treatment and control groups (i.e., after the one-to-one matching, the treatment and control groups still significantly differed on the variable "total number of patients"). The one-to-one matching did not generate any materially different results in any of the subsequent analyses with or without controlling for the total number of patients. We also used different matching algorithms (e.g., nearest neighborhood without calipers). None of these alternative matching algorithms generated materially different results.

Table 6. Alternative Instruments with Month Fixed Effects

	Diabetes		*Depression*	
Dependent Variable	***Physicians' Post***	***Patients' Post***	***Physicians' Post***	***Patients' Post***
Column	**(1)**	**(2)**	**(3)**	**(4)**
Patients' post	.070 (.106)		.123* (.062)	
Physicians' post		.247* (.119)		.229** (.081)
Physicians' reputation	-.007 (.046)	-.052** (.020)	-.008 (.023)	-.060* (.026)
Total # of patients	.011 (.018)	.026*** (.008)	.001 (.009)	.035*** (.007)
Time FE	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Robust clustered error	Yes	Yes	Yes	Yes
No. of physicians	262	360	300	395
F-value	2.30*	3.66***	8.74***	9.57***
DiagnosticTests				
Hansen test of overid. Restrictions χ^2	9.44	6.96	5.77	6.30

Notes: 1. Windmeijer corrected standard errors are reported in parentheses. 2. The p-values read as follow: *p < 0.05; **p < 0.01; ***p < 0.001.

Table 7. Summary Statistics and Covariate Comparison Before and After Matching

		diabetes2012			*diabetes2014*			*depression2012*			*depression2014*		
		Mean		*T-value*	*Mean*		*T-value*	*Mean*		*T-value*	*Mean*		*T-value*
Variable		***Treat-ment***	***Control***		***Treat-ment***	***Control***		***Treat-ment***	***Control***		***Treat-ment***	***Control***	
title	Before	.630	.529	2.79	.611	.478	4.22	.567	.466	2.70	.544	.420	3.72
	After	.620	.580	.76	.561	.588	-.55	.497	.518	-.39	.494	.443	1.19
level	Before	.889	.827	2.36	.881	.814	2.84	.867	.803	2.27	.851	.796	2.13
	After	.871	.812	1.51	.858	.851	.22	.860	.833	.68	.827	.885	-1.93
gdp2012	Before	8.802	8.430	5.13				9.010	8.777	3.60			
	After	8.754	8.676	.78				8.878	9.020	-1.63			
gdp2014	Before				8.997	8.621	6.06				9.179	8.940	4.20
	After				8.912	8.926	-.15				9.093	9.163	-1.06
reputation	Before	.725	.511	6.41	.740	.579	5.73	.707	.586	3.77	.734	.614	4.36
	After	.669	.632	.77	.666	.671	-.12	.653	.698	-1.03	.696	.746	-1.51
totalpatients	Before	5.225	1.259	35.72	5.360	1.208	43.01	5.687	1.754	33.97	5.808	1.792	35.49
	After	4.348	4.324	.18	4.270	4.252	.14	4.685	4.647	.30	4.960	4.913	.36
No. of physicians	Before	262	671		360	823		300	436		395	509	
	After	171	671		219	823		171	436		271	509	

Difference-in-Differences Analysis: Our datasets have three pre-treatment and three post-treatment periods. We ran DD models with all pre- and post-treatment periods based on the leads and lags specification (Autor 2003):

$$wellbeing_{it} = \alpha_i + \delta_t + \sum_{\tau=-2}^{-1} \beta_\tau D_{i\tau} + \sum_{\tau=1}^{3} \beta_\tau D_{i\tau} + \beta_4 reputation_{it} + \beta_5 totalpatients_{it} + \varepsilon_{it} \quad (3)$$

$$relationsip_{it} = \alpha_i + \delta_t + \sum_{\tau=-2}^{-1} \beta_\tau D_{i\tau} + \sum_{\tau=1}^{3} \beta_\tau D_{i\tau} + \beta_4 reputation_{it} + \beta_5 totalpatients_{it} + \varepsilon_{it} \quad (4)$$

where α_i and δ_t are physician and month fixed effects, and $D_{i\tau}$ are a series of dummy variables indicating whether physician i's patients or physician i received the "treatment" in month τ (τ = -1 and -2 indicate the first two pre-treatment months, the last pre-treatment month is used as the reference and thus is omitted from the models, and τ = 1, 2, and 3 indicate the three post-treatment months). We controlled for patient-generated ratings of satisfaction with physician i at the end of month t ($reputation_{it}$) and the total number of patients who had consulted with physician i by the end of month t ($totalpatients_{it}$).

We ran the DD models on four datasets (i.e., two chronic diseases × two treatment events). Table 8 summarizes the results of DD estimation. In all these models, the "treatment" effects in the three post-treatment periods are captured by the coefficients of D_{i1}, D_{i2}, and D_{i3}.

We assessed the effects of patients' participation in physicians' OHC on patient well-being and the patient–physician relationship via the first treatment event (i.e., the launch of the mobile app leading to less patient participation). The effect of reduced patient participation on patient well-being is significantly negative in all three post-treatment months for both diabetes (columns 1–2) and depression (columns 9–10). The effect of reduced patient participation on the patient–physician relationship is significantly negative in the first post-treatment month but does not persist beyond the first post-treatment month for either diabetes (columns 3–4) or depression (columns 11–12). We similarly assessed the effects of physician participation in their OHC on patient well-being and the patient–physician relationship via the second treatment event (i.e., announcement that encourages physicians' participation). The effect of increased physician participation on patient well-being is more persistent for depression than for diabetes: the effect is significantly positive only in the first post-treatment month for diabetes (columns 5–6) but is significantly positive in the first two post-treatment months for depression (columns 13–14). The effect of increased physician participation on the patient–physician relationship is significantly positive only in the first post-treatment month for both diabetes (columns 7–8) and depression (columns 15–16).

Difference-in-Differences Identifying Assumption and Placebo Tests

The validity of DD analysis depends on the identifying assumption that the treatment and control groups have parallel trends in the outcome variables in the absence of treatment (Angrist and Pischke 2008). To verify this assumption, we plotted the treatment effects (and their 95% confidence intervals) in the pre- and post-treatment periods (see Figure B1 in Appendix B). Since the treatment effects in the pre-treatment periods capture the difference-in-differences in the outcome variables between the two groups in the pre-treatment periods, parallel trends in the pre-treatment periods require all treatment effects in the pre-treatment periods to be insignificantly different from zero. Figure B1 shows that in all of these DD models, none of the treatment effects in the pre-treatment periods are significantly different from zero. We also ran a series of F-tests to test the null hypothesis that the treatment effects in the pre-treatment periods are jointly zero for each of the DD models. None of the F-tests reject the null hypothesis. Therefore, we conclude that the treatment and control groups may have similar trends in the absence of treatment.

We further ran a series of placebo tests to assess the credibility of our DD analysis. Specifically, we place a "placebo event" at arbitrary times prior to the actual treatment events. The placebo event should not have significant effects on the outcome variables immediately after the placebo event. We ran a series of DD models with one-month period before and after the placebo event. The results show that the placebo event is nonsignificant in all of these models (Table B1 in Appendix B). From this analysis, we conclude that the DD analysis generates credible causal evidence.

Additional Analyses for the DD Approach: Heterogeneous Treatment Effects

The DD analyses in the preceding section estimate the average treatment effects; that is, the effects of patients' or physicians' participation in the OHC on patient well-being and the patient–physician relationship averaged across all physicians in the sample. It is possible that these effects are heterogeneous across different physicians because they are not equally affected by the two treatment events.

Table 8. Impact of Patients' and Physicians' Participation on Patient Well-Being and the Physician–Patient Relationship

Disease	Diabetes								Depression							
	Treatment Event 1: Launch of mobile app leading to less patients' participation				Treatment Event 2: Announcement that encourages physicians' participation				Treatment Event 1: Launch of mobile app leading to less patients' participation				Treatment Event 2: Announcement that encourages physicians' participation			
Dependent variable	wellbeing		relationship		wellbeing		relationship		wellbeing		relationship		wellbeing		relationship	
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
D_{i1}	-.078* (.036)	-.079* (.036)	-.046* (.021)	-.047* (.020)	.079* (.037)	.078* (.037)	.038* (.018)	.037* (.018)	-.129* (.064)	-.132* (.064)	-.048* (.020)	-.049* (.020)	.206* (.099)	.205* (.099)	.063* (.028)	.063* (.028)
D_{i2}	-.068* (.035)	-.069* (.035)	-.017 (.028)	-.019 (.028)	.038 (.042)	.036 (.042)	.040 (.028)	.039 (.028)	-.090* (.036)	-.093** (.036)	-.001 (.027)	-.002 (.027)	.072* (.035)	.076* (.035)	.048 (.027)	.048 (.027)
D_{i3}	-.075* (.037)	-.079* (.037)	-.002 (.026)	-.005 (.026)	.034 (.050)	.031 (.050)	.040 (.027)	.038 (.027)	-.133* (.054)	-.136* (.053)	-.049 (.045)	-.050 (.045)	-.129 (.121)	-.124 (.122)	.022 (.037)	.022 (.037)
$D_{i,-1}$	.025 (.037)	.025 (.037)	-.087 (.055)	-.085 (.054)	.058 (.040)	.057 (.040)	-.003 (.025)	-.003 (.025)	-.062 (.070)	-.060 (.070)	-.042 (.026)	-.041 (.026)	.137 (.102)	.141 (.100)	.048 (.028)	.048 (.028)
$D_{i,-2}$	.005 (.055)	.005 (.055)	-.056 (.033)	-.056 (.033)	.038 (.046)	.035 (.046)	.010 (.034)	.009 (.035)	-.119 (.070)	-.111 (.071)	-.081 (.043)	-.078 (.043)	.164 (.101)	.170 (.099)	.046 (.028)	.046 (.028)
Reputation		.151 (.093)		.066 (.085)		.470*** (.097)		.180 (.120)		.165 (.121)		.062 (.036)		.694*** (.198)		.044 (.026)
Total patients		.008 (.023)		.035* (.015)		-.002 (.023)		.008 (.019)		.030 (.035)		.016 (.010)		-.148 (.086)		.006 (.016)
Physician FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Robust clustered error	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. of physicians	842	842	842	842	1042	1042	1042	1042	607	607	607	607	780	780	780	780
R-Squared	.430	.430	.624	.625	.292	.302	.546	.548	.360	.362	.560	.561	.372	.388	.508	.508

Notes: ***p < 0.001; **p < 0.01; *p < 0.05

We examine if the treatment effects vary with physician characteristics based on a difference-in-difference-in-differences (DDD) specification (e.g., Gruber 1997; Rishika et al. 2013):

$$wellbeing_{it} = \alpha_i + \delta_t + \beta_1 * D_{i1} + \beta_2 * D_{i1} * M_i + \beta_3 * reputation_{it} + \beta_4 * totalpatients_{it} + \varepsilon_{it} \quad (5)$$

$$relationship_{it} = \alpha_i + \delta_t + \beta_1 * D_{i1} + \beta_2 * D_{i1} * M_i + \beta_3 * reputation_{it} + \beta_4 * totalpatients_{it} + \varepsilon_{it} \quad (6)$$

where M_i is a variable along which a treatment effect may vary and β_2 is the treatment heterogeneity coefficient that captures the degree to which the treatment effect varies with M_i. We examine if the treatment effects vary across five physician characteristics including physician's title (i.e., $M_i = 1$ when physician i is a "chief physician"), physician's hospital rank (i.e., $M_i = 1$ when physician i is from the highest-ranked hospital), GDP of the city where a physician is located, patient-generated rating of their satisfaction with the physician before the treatment event, and the total number of patients who had consulted a physician before the treatment event. We report the treatment heterogeneity coefficient β_2 in Table C1 in Appendix C.[8] It can be seen that the effect of physicians' participation on patient well-being varies with physician title and GDP of the city where the physician is located. The participation of chief physicians and physicians from higher GDP cities has a greater impact on patient well-being. Chief physicians in China are typically more experienced than other physicians in the same hospital. Their participation in the OHC may provide patients with high-quality medical and clinical information, which leads to the greater impact on patient well-being. There is a strong asso-

[8]We only report the treatment effect heterogeneity in the first period following the treatment event. There is no significant treatment effect heterogeneity in the second and third post-treatment event periods.

ciation between GDP and the availability of high-quality care (Cutler 2002). Physicians from the cities with higher GDP in general have stronger medical expertise than physicians from less-developed areas. Therefore, their participation in the OHC may also have a greater impact on patient well-being. Further, the participation of physicians from higher GDP cities has a greater impact on the patient–physician relationship but the participation of chief physicians does not. The majority of physicians on the platform are chief physicians (more than 53.6% of the physicians are chief physicians in our sample). Therefore, when choosing physicians for consultation, patients might be more sensitive to the socioeconomic development of the physicians' location (e.g., GDP) than to the chief physician status. Given that our patient–physician relationship is operationalized via patients' choice of physicians, this might explain why the effect of physicians' participation on the patient–physician relationship varies with GDP of the physicians' city but not the chief physician status. The findings here also reflect differences between diabetes and depression. Depression is a psychiatric disorder where interpersonal therapy and psychotherapy (i.e., a patient talks with a health professional about his or her thoughts and feelings) play an important role in treatment (Keller et al. 2000). The opportunities for communicating with physicians might be more important than the background of the physicians in generating positive effects on patient well-being and the patient–physician relationship. This might explain why the treatment effects do not vary with physician characteristics for depression.

Discussion

In this section, we first summarize our findings. We then elaborate the mechanisms that may account for the differences between the empirical findings and our theoretical model. We particularly focus on discussing how the links in our theoretical model may vary with contextual factors. The objective of this discussion is to generate further theoretical insights to enrich our model and elucidate the generalizability of our findings.

Summary of the Findings

We find that physicians' participation in their OHC increases patients' participation for both diabetes and depression (H1), but patients' participation has a significant impact on physicians' participation only for depression (H2).

Further, physicians' participation in their OHC has a significant effect on patient well-being for both diabetes and depression (H3). Such an effect seems more persistent for depression than for diabetes; for diabetes, the effect is only significant in the first month following the treatment event, but for depression, the effect is significant in the two months following the treatment event. We also find that physicians' participation in their OHC has a significant but transient effect on the patient–physician relationship for both diabetes and depression (H4). This effect is only significant in the first post-treatment month for both diabetes and depression.

Our analysis further shows that patients' participation in the physician-driven OHC has a significant and persistent effect on patient well-being for both diabetes and depression (H5). We also find a significant but transient effect of patients' participation in their physician's OHC on the patient–physician relationship for both diabetes and depression (H6). The effect is only significant in the first post-treatment period.

The Importance of Contextual Factors

While most of our hypotheses are supported, there are a few notable differences between the empirical findings and the theoretical model. A possible reason for these differences is that the links in our theoretical model may vary with contextual factors. Considering the research context and our findings, we suggest that important contextual factors include the nature of the disease, difference in roles, time commitments, incentives of physicians vis-à-vis patients, and the regulatory regime governing the online interactions between patients and physicians.

First, the nature of the disease leads to asymmetries in terms of the effects for diabetes versus depression. Our findings show that physicians' participation in the OHC has a more persistent effect on patient well-being for depression than for diabetes. This may pertain to the importance of interpersonal therapy and psychotherapy in treating depression (Keller et al. 2000). A physician-driven OHC might be more suited to the management of psychiatric diseases due to the therapeutic value of interpersonal communication for these diseases.

Second, the difference in patients' and physicians' roles also leads to asymmetries in the effects of patients' versus physicians' participation on patient well-being. Our findings show that patients' participation in the OHC has more persistent effects on patient well-being than physicians' participation (for both diabetes and depression). In the traditional healthcare model, patients play a more passive role in that they often expect health professionals to tell them what to do during the course of a disease. However, the more recent chronic care model suggests that patient activation is important in the self-management of chronic disease (Bodenheimer et al. 2002). This means that patients should take primary responsibility for their care.

Third, the differences in patients' versus physicians' time commitments and incentives can also affect the links in the theoretical model. The online consultation platform allows patients greater time flexibility to access doctors from the best public hospitals in major Chinese cities. Online consultation is also much more affordable than traditional hospital visits. Further, thanks to the Internet plus program, both the government-owned and private insurance companies are expanding their health insurance coverage to reimburse online medical consultations (Xie et al. 2017). This creates a strong incentive for patients to take advantage of online medical consultations and the accompanying OHC. In contrast, most physicians are salaried employees of public hospitals, and typically overloaded and underpaid. Online consultation is a paid service, but participating in the OHC is free of charge once a patient becomes a member of the OHC. As such, while online consultations may provide physicians with a meaningful stream of extra income, they are not compensated monetarily for their participation in the OHC. Therefore, although we hypothesized a mutual impact between patients' and physicians' participation in the OHC, the differences in patients' versus physicians' time commitment and incentives may cause the asymmetry in the mutual impact. We find asymmetry in the mutual impact between patients' and physicians' participation for diabetes but not depression (i.e., while physicians' participation prompts patients' participation for both diabetes and depression, patients' participation prompts physicians' participation for depression but not diabetes). This is likely due to a combination of the OHC's policy and the psychiatric nature of depression. Since physicians are not compensated monetarily for their participation in the OHC, their participation is voluntary and only motivated by reputational gains and/or altruism. Given that their participation is voluntary, physicians may be prompted to participate by specific characteristics of the chronic condition. Patients with depression are often at a higher risk of self-harm or suicide (Harrington 2001). These patients' activities in the OHC may require their physicians' immediate attention. Therefore, physicians who treat depression may be more likely to respond to patients' communication needs in the OHC.

Finally, the regulatory regime governing privacy and patient information also affects the links in our theoretical model by constraining the online interactions between patients and health professionals. Until May 2018, there was no unified online privacy and personal data law in China. Principles and rules relating to privacy and cybersecurity could be found in industry-specific laws, regulations, and local provisions. Lack of clear legal guidance is one reason why Chinese health professionals are unwilling to participate in telemedicine (Cai et al. 2016). Therefore, physicians may limit their interactions with patients in the OHC due to the legal uncertainties regarding patient privacy protection.

Considering these contextual factors not only enriches our theoretical model but generates insights that may inform policies and design of the OHC. For example, while the affordability of the online consultation and the new medical insurance reimbursement scheme provide strong incentives for patients to choose online consultations, physicians are not compensated monetarily for their participation in the OHC. The online platform may consider using monetary incentives to encourage physicians' participation. Based on our argument that physicians' participation can be motivated by social rewards (e.g., reputation gains) and concern for self-image, the online platform may also implement a reputation system, which allows patients to rate how actively the physicians participate in the OHC. Further, given the rapid expansion of the online medical consultation market and the legal uncertainties regarding personal data not only in China but in other countries as well, legal authorities may consider issuing clear guidance on online patient data protection. This may remove an important barrier to physicians' participation in the OHC.

Considering these contextual factors generates a better understanding of the generalizability of our model. The robust growth of online medical consultation and the physician-driven OHC is deeply rooted in the Chinese context. When applying the model to other contexts, it is important to consider the contextual factors outlined in this discussion.

Limitations and Future Research

Our research has several limitations. First, as discussed in the hypotheses development, physicians and patients participate in the OHC in various ways (e.g., instrumental and socio-emotional communication). Different types of participation may have differential effects on the outcomes of interest. Future research may investigate how different types of participation influence outcomes differently. Second, to protect patient privacy, the OHC does not display any patient identity information. As a result, though we can see how many online *consultations* with the physician each patient has, we were unable to identify how frequently each patient participates in an OHC. Investigating these richer participation patterns would generate a more granular understanding of the effects of physician-driven OHC. Finally, our measure of patient well-being and the patient–physician relationship may suffer from measurement errors and selection bias. We rely on patients' self-reports to measure patient well-being. In our sample, approximately 27% of patients self-reported their health status. The percentage of patients self-reporting their health status may vary with physician or patient characteristics (e.g., some physicians are more likely to encourage their patients to report than other physicians and some patients are more likely to report than other patients) or an interaction of the two, which may also contribute to the patient–physician relationship and patient well-being. While this selection bias is limited by using the physician fixed effects and the DD approach, further research may search for data sources that have more complete patient well-being information. Similarly, instead of directly measuring the patient–physician relationship (e.g., using survey data), we use an indirect behavioral measure (i.e., their choice of paying a physician for further consultations), which is susceptible to various contextual factors. While the impact of the measurement error is alleviated by our econometrics procedures, including the fixed effects, controls, and the DD analysis, future research may develop alternative measures to directly address the measurement issue.

Contributions

This research makes several contributions to the literature. First, much prior research has examined patient-oriented OHC. Our research extends the current literature to include physician-driven OHC, a social media application that engages both patients and their physicians. We believe that physician-driven OHC is a fertile ground for future research. The richness of activities (e.g., interactions between peer-patients and between patients and their physicians) and information (e.g., physicians' medical expertise, patients' experiential knowledge, and emotional support) in a physician-driven OHC creates many opportunities for theory development and empirical analyses. While our research focuses on patient well-being and the patient–physician relationship, future research may examine physician-level outcomes such as physician learning, physician productivity, physicians' reputation and branding, and so on. Researchers may also investigate the effects of physician-driven OHC from different theoretical perspectives. For example, in a physician-driven OHC, social comparison between patients may be prevalent due to the high degree of experiential similarity between patients (i.e., patients in the OHC are not only managing the same disease, they have also consulted with or been treated by the same physician) (Suls et al. 2002). Social comparison between patients will likely influence both patient outcomes (e.g., seeing others coping well with the condition can provide hope) and physician behaviors (e.g., a physician may refine his or her treatment plan because of patients' social comparison). Therefore, social comparison is a potentially useful theoretical lens to understand the effects of physician-driven OHC.

Second, drawing on the patient–physician partnership paradigm, we develop a conceptual framework and elaborate the theoretical mechanisms that explain how physician-driven OHC facilitates patient–physician collaborative care and self-management support, leading to improved patient well-being and patient–physician relationships. Future research may take advantage of the rich qualitative information in physician-driven OHC to test the theoretical mechanisms posited in our research. For example, analyzing the qualitative contents of patient posts may help researchers generate fine-grained evidence of how patients are motivated to participate in the OHC in response to peer-patients' and physicians' activities.

Third, while many prior studies only look at one disease (e.g., Goh et al. 2016; Yan 2018; Yan and Tan 2014), we examine two diseases of different nature. Our findings show that the effects of OHC participation vary with the nature of the disease. This highlights the importance of theorizing and testing the effects of contextual factors in this research context. Future research may test how the effects of participating in OHC on health outcomes vary with contextual factors such as the nature of the disease, time commitments and incentives of the participants, and regulatory regime governing the interactions.

Fourth, this research focuses on generating credible causal evidence for the effects of OHC in healthcare. Methodological challenges such as self-selection and reverse causality biases are likely prevalent in assessing the effects of OHC in healthcare. For example, the association between participation in an OHC and health outcomes does not necessarily mean that OHC use improves health outcomes. A feasible alternative explanation is that patients who experienced improved health outcomes are more likely to use OHC to share their experiences with peer-patients. Findings that are open to different interpretations are not particularly helpful to inform policy making. Though randomized controlled trials are considered the "gold standard" in assessing causal effects, they are extremely expensive to implement. Our research addresses causal inference by exploiting "natural experiments" from observational data. This represents a fruitful direction to assess the causal effects of OHC in healthcare.

Our findings also have practical contributions. First, continuous communication and strong partnerships between patients and health professionals are key to the effective management of chronic diseases. Although there may be a number of ways to improve these, our research shows that physician-driven OHC is an effective and sustainable means to strengthen the partnership between patients and their physicians.

Second, given the large and increasing number of chronic disease patients worldwide and the long-term burden of these diseases, policy makers may consider physician-driven OHC as a solution to lowering the burden on the healthcare system.

Finally, our finding that patients' and physicians' participation in physician-driven OHC improves patient–physician relationships may also have useful implications. Improving patient–physician relationships is an important social issue in China: the average number of physical attacks on doctors increased from 20.6 per hospital in 2008 to 27.3 per hospital in 2012 (Burkitt 2013). At the core of this issue is the strained relationship between patients and their physicians. Our research suggests that physicians in China may leverage OHC to improve relationships with their patients.

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Appendix A

Month-by-Month Descriptive Statistics and Correlations

Table A1. Month-by-Month Descriptive Statistics

Variable	*diabetes2012*	*diabetes2014*	*depression2012*	*depression2014*
The first month prior to the treatment event				
$relationship_{it}$	.079 (.221)	.034 (.147)	.065 (.177)	.058 (.189)
$wellbeing_{it}$	.105 (.300)	.070 (.254)	.128 (.328)	.112 (.315)
$patient\_post_{it}$	1.992 (29.825)	.067 (.968)	4.158 (36.741)	.147 (1.184)
$physician\_post_{it}$	.096 (.930)	.015 (.209)	.147 (1.100)	.046 (.473)
$reputation_{it}$	.570 (.469)	.621 (.455)	.632 (.433)	.655 (.420)
$totalpatients_{it}$	152.492 (527.354)	223.788 (789.116)	292.625 (745.623)	460.523 (1222.124)
The second month prior to the treatment event				
$relationship_{it}$	.079 (.220)	.029 (.127)	.071 (.179)	.060 (.183)
$wellbeing_{it}$	.114 (.311)	.071 (.255)	.143 (.343)	.106 (.308)
$patient\_post_{it}$	1.835 (35.447)	.083 (1.666)	4.484 (44.316)	.171 (2.012)
$physician\_post_{it}$	.069 (.746)	.011 (.120)	.195 (1.362)	.073 (1.372)
$reputation_{it}$	.572 (.469)	.624 (.454)	.634 (.432)	.658 (.418)
$totalpatients_{it}$	7675.594 (543.762)	225.131 (794.937)	301.270 (766.005)	462.285 (1232.058)
The third month prior to the treatment event				
$relationship_{it}$	.059 (.188)	.030 (.132)	.092 (.222)	.058 (.177)
$wellbeing_{it}$	.061 (.231)	.062 (.242)	.114 (.311)	.112 (.314)
$patient\_post_{it}$	2.625 (51.741)	.078 (1.625)	4.885 (61.090)	.231 (2.115)
$physician\_post_{it}$	.183 (2.792)	.007 (.082)	.114 (1.058)	.027 (.234)
$reputation_{it}$	.571 (.469)	.628 (.452)	.636 (.431)	.666 (.414)
$totalpatients_{it}$	163.168 (559.331)	225.759 (799.058)	309.919 (788.273)	464.626 (1242.932)

The first month after the treatment event				
relationship$_{it}$	.067 (.198)	.027 (.115)	.085 (.206)	.049 (.155)
wellbeing$_{it}$	.099 (.293)	.051 (.220)	.153 (.355)	.087 (.281)
patient_post$_{it}$	2.109 (42.575)	.102 (1.753)	3.276 (47.922)	.186 (2.073)
physician_post$_{it}$	.083 (1.068)	.030 (.417)	.102 (.792)	.080 (1.002)
reputation$_{it}$	.575 (.468)	.631 (.451)	.645 (.428)	.667 (.413)
totalpatients$_{it}$	171.027 (579.098)	228.899 (808.656)	323.269 (815.711)	469.630 (1256.616)
The second month after the treatment event				
relationship$_{it}$	.072 (.214)	.034 (.143)	.084 (.206)	.056 (.170)
wellbeing$_{it}$	.087 (.277)	.078 (.268)	.128 (.329)	.101 (.298)
patient_post$_{it}$	1.518 (28.965)	.125 (2.182)	2.162 (32.104)	.313 (2.858)
physician_post$_{it}$	.064 (.630)	.052 (.310)	.096 (.779)	.207 (1.534)
reputation$_{it}$	.583 (.466)	.640 (.448)	.651 (.426)	.670 (.411)
totalpatients$_{it}$	178.394 (599.397)	232.254 (817.454)	336.143 (842.165)	474.662 (1269.558)
The third month after the treatment event				
relationship$_{it}$	.074 (0.210)	.034 (.144)	.082 (.205)	.056 (.179)
wellbeing$_{it}$	.093 (.285)	.062 (.240)	.119 (.320)	.104 (.305)
patient_post$_{it}$	1.433 (32.286)	.087 (1.640)	2.319 (36.606)	.229 (2.139)
physician_post$_{it}$	.078 (0.756)	.055 (.318)	.095 (.800)	.206 (1.383)
reputation$_{it}$	.587 (.465)	.643 (.447)	.656 (.423)	.676 (.409)
totalpatients$_{it}$	186.069 (618.498)	234.939 (823.747)	350.457 (871.742)	479.472 (1283.025)

Notes: 1. This table does not include the time-invariant variables (gdp_i, $title_i$ and $level_i$).
2. The mean values and the standard deviations (in the parentheses) are in the cells.

Table A2. Correlation Matrix

	Dibetes2012								
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
$relationship_{it}$	1								
$wellbeing_{it}$	.368	1							
$patient\_post_{it}$	.156	.122	1						
$physician\_post_{it}$	.038	.064	.034	1					
$reputation_{it}$	.185	.210	.035	.036	1				
$totalpatients_{it}$	.225	.319	.356	.287	.173	1			
$gdp2012_{i}$	.237	.181	.067	.035	.179	.139	1		
$title_{i}$	.097	.087	.037	.031	.219	.079	.021	1	
$level_{i}$	.114	.074	.019	-.005	.088	.047	.103	.077	1
	Dibetes2014								
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
$relationship_{it}$	1								
$wellbeing_{it}$	.337	1							
$patient\_post_{it}$	.061	.112	1						
$physician\_post_{it}$	.070	.084	.122	1					
$reputation_{it}$	.113	.148	.032	.055	1				
$totalpatients_{it}$	.212	.235	.311	.252	.138	1			
$gdp2014_{i}$	.147	.134	.068	.036	.155	.139	1		
$title_{i}$	.074	.060	.034	.045	.202	.082	.0003	1	
$level_{i}$	.057	.069	.021	.032	.053	.045	.095	.062	1
	Depression2012								
Variable	1	2	3	4	5	6	7	8	9
$relationship_{it}$	1								
$wellbeing_{it}$	.297	1							
$patient\_post_{it}$	.171	.139	1						
$physician\_post_{it}$	.036	.093	.145	1					
$reputation_{it}$	.103	.186	.044	.035	1				
$totalpatients_{it}$	.184	.359	.323	.227	.152	1			
$gdp2012_{i}$	.172	.119	.062	.060	.113	.132	1		
$title_{i}$	.113	.128	.027	-.026	.174	.111	.006	1	
$level_{i}$	.109	.101	.007	.035	.055	.059	.225	.065	1
	Depression2014								
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
$relationship_{it}$	1								
$wellbeing_{it}$	.234	1							
$patient\_post_{it}$	.066	.124	1						
$physician\_post_{it}$	.024	.056	.077	1					
$reputation_{it}$	.099	.164	.050	.046	1				
$totalpatients_{it}$	.160	.256	.329	.172	.131	1			
$gdp2014_{i}$	.142	.111	.071	.021	.097	.146	1		
$title_{i}$	.120	.095	.029	.031	.179	.116	.012	1	
$level_{i}$	.067	.072	.016	-.015	.080	.061	.22	.042	1

Appendix B

Tables and Figures for Difference-in-Differences Identifying Assumption and Placebo Tests

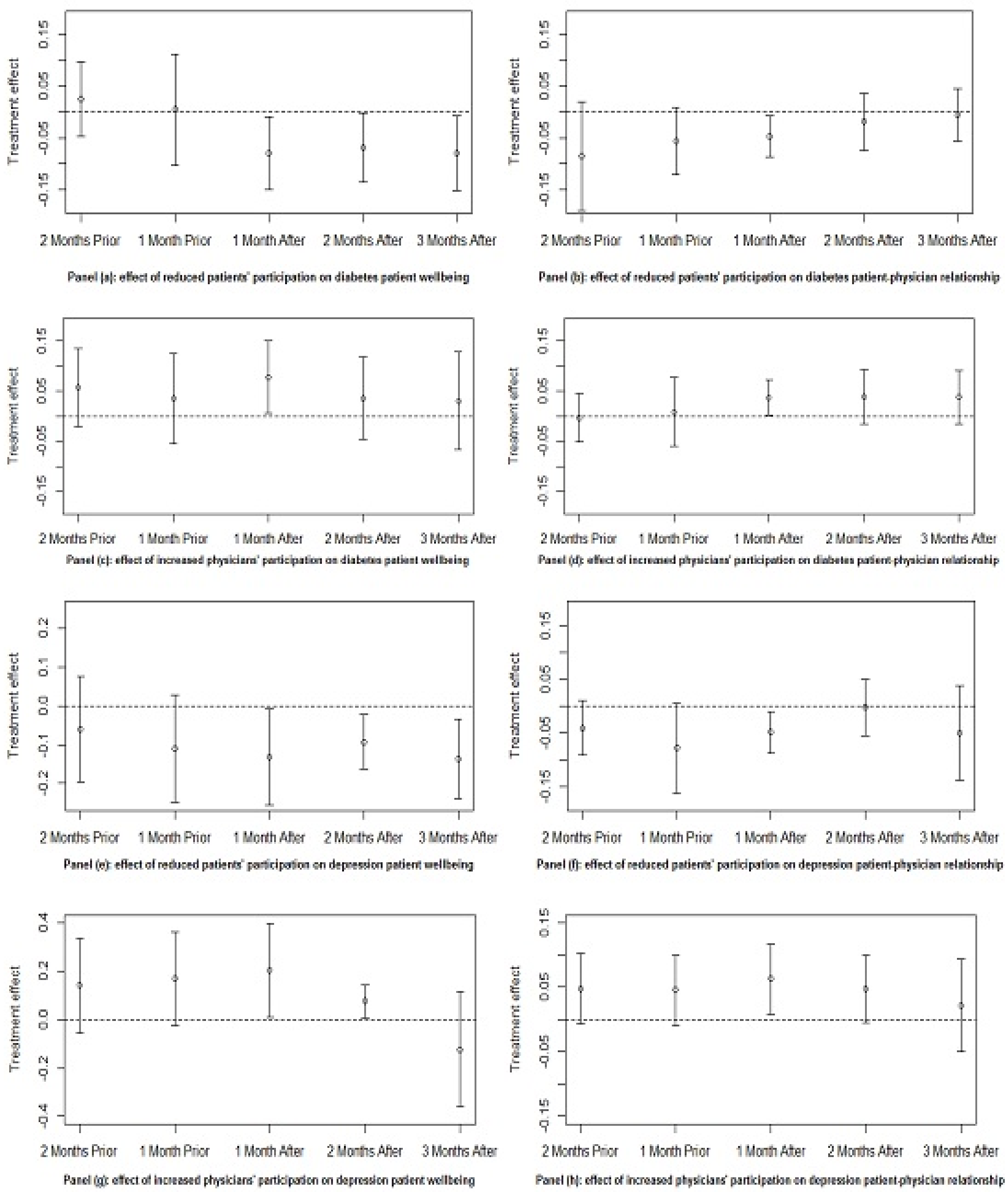

Figure B1. Treatment Effects Over Time

Table B1. DD Placebo Analysis

	Diabetes							
	Treatment Event 1: Launch of mobile app leading to less patients' participation (actual date: May 22 2012)				Treatment Event 2: Announcement that encourages physicians' participation (actual date: July 1 2014)			
Placebo event date	March 22 2012		April 22 2012		May 1 2014		June 1 2014	
Dependent variable	wellbeing	relation-ship	wellbeing	relation-ship	wellbeing	relation-ship	wellbeing	relation-ship
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Treatment effect	.021 (.058)	-.031 (.060)	-.028 (.037)	.085 (.054)	.022 (.038)	-.012 (.049)	-.056 (.040)	.002 (.025)
Control variable	Y	Y	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Robust clustered error	Y	Y	Y	Y	Y	Y	Y	Y
	Depression							
	Treatment Event 1: Launch of mobile app leading to less patients' participation (actual date: May 22 2012)				Treatment Event 2: Announcement that encourages physicians' participation (actual date: July 1 2014)			
Placebo event date	March 22 2012		April 22 2012		May 1 2014		June 1 2014	
Dependent variable	wellbeing	relation-ship	wellbeing	relation-ship	wellbeing	relation-ship	wellbeing	relation-ship
Column	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
Treatment effect	.057 (.087)	.035 (.042)	.057 (.069)	.041 (.026)	-.032 (.036)	.001 (.021)	-.145 (.097)	-.049 (.028)
Control variable	Y	Y	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Robust clustered error	Y	Y	Y	Y	Y	Y	Y	Y

Notes: ***p < 0.001; *p < 0.01; *p < 0.05

Appendix C

Heterogeneous Treatment Effects Analysis

Table C1. Heterogeneous Treatment Effects

Disease	Diabetes									
	Treatment Event 1: Launch of mobile app leading to less patients' participation					Treatment Event 2: Announcement that encourages physicians' participation				
	title	level	gdp	reputation	totalpatients	title	level	gdp	reputation	totalpatients
Variable	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$
	wellbeing									
Coefficient	-.030 (.056)	.031 (.085)	.046 (.033)	-.029 (.051)	.009 (.017)	.069* (.032)	.025 (.020)	.041* (.021)	.033 (.027)	.007 (.014)
	relationship									
Coefficient	.006 (.034)	.002 (.022)	.009 (.016)	.007 (.034)	-.004 (.007)	.009 (.020)	.018 (.014)	.019* (.009)	.002 (.015)	-.001 (.007)
No. of physicians	842	842	842	842	842	1042	1042	1042	1042	1042
Disease	**Depression**									
	Treatment Event 1: Launch of mobile app leading to less patients' participation					Treatment Event 2: Announcement that encourages physicians' participation				
	title	level	gdp	reputation	totalpatients	title	level	gdp	reputation	totalpatients
Variable	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$	$D_{i1}*M_i$
	wellbeing									
Coefficient	-.044 (.067)	-.048 (.070)	-.048 (.032)	-.012 (.060)	.037 (.030)	.035 (.041)	.051 (.035)	.024 (.025)	.036 (.032)	.016 (.013)
	relationship									
Coefficient	-.012 (.035)	-.036 (.033)	-.016 (.017)	.060 (.042)	.022 (.013)	.002 (.025)	-.003 (.027)	.016 (.013)	.051 (.027)	.008 (.008)
No. of physicians	607	607	607	607	607	780	780	780	780	780
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Robust clustered error	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: ***p < 0.001; **p < 0.01; *p < 0.05