UNDERSTANDING RESILIENCE OF PHYSICIAN-DRIVEN ONLINE HEALTHCARE COMMUNITIES UNDER EXOGENOUS SHOCK

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ABSTRACT

The COVID-19 pandemic has underscored the urgent need for healthcare entities to develop resilient strategies to cope with disruptions caused by the pandemic. This study focuses on the digital resilience of certified physicians who adopted online healthcare communities (OHCs) to acquire patients and conduct telemedicine services in the pandemic. We synthesized the resilience literature and identified two effects of digital resilience: the resistance effect and the recovery effect. We collected a proprietary dataset that matches online and offline data sources to study the digital resilience of physicians. A difference-in-differences (DID) analysis shows that physicians who adopted an OHC had strong resistance and recovery effects in the pandemic. In particular, these physicians had 46.2% less reduction in medical consultations in the immediate period and 29.7% more bounce back in the subsequent period, respectively, after the COVID-19 outbreak than physicians who did not adopt an OHC. We further analyzed the sources of physicians' digital resilience by distinguishing between new and existing patients from both online and offline channels. Our subgroup analysis shows that, in general, digital resilience is more pronounced when physicians have stronger online reputations or more positive interactions with patients on the OHC platform, providing further support of the mechanisms underlying digital resilience. Our research has significant theoretical and managerial implications that extend beyond the pandemic context.

Keywords: digital resilience, resistance effect, recovery effect, online healthcare community, COVID-19 pandemic, natural experiment

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CHAPTER 1. INTRODUCTION

Recent information systems (IS) studies have found that many entities apply digital technologies as a means of bolstering resilience to disruption events, which the literature refers to as *information technology resilience* or *digital resilience* (e.g., Park et al. 2015; Shin et al. 2012). For example, to address a typical disruption in the healthcare management domain—outpatient overcrowding, hospitals encourage physicians to join online healthcare platforms (e.g., mdlive.com); such platforms enable physicians to make professional diagnoses and write prescriptions and enable patients to access competent online healthcare services.[1] In today's turbulent environment, healthcare entities are particularly susceptible to various disruption events, such as healthcare supply chain disruptions, healthcare data breaches, and severe overcrowding in outpatient departments (e.g., Bhakoo and Choi 2013; Davis et al. 2020; Kwon and Johnson 2014). As such, developing resilient strategies to effectively manage and cope with disruptions is of paramount importance for healthcare entities (Achour and Price 2010).[2]

Although current IS studies have examined digital resilience in the healthcare domain, these studies have primarily been conducted in contexts where digital technologies are applied to build resilience to cope with predictable disruptions (e.g., disruptions that have happened before) (e.g., Davis et al. 2020; Kwon and Johnson 2013). For example, when outpatient overcrowding occurs during influenza season, physicians can increase their usage of online platforms (e.g., the telemedicine) to mitigate such overcrowding (Metzger and Flanagin 2011). Therefore, information systems can improve resilience by reducing the reoccurrence probability of identical disruptions

[1] Please see https://pwcc.upenn.edu/en/hospital-overcrowding-a-global-problem/, accessed in June 2021.
[2] Please see https://www.mckinsey.com/business-functions/operations/our-insights/building-resilient-operations, accessed in June 2021.

(Ambulkar et al. 2015). However, when facing disruptions caused by unpredictable and unprecedented exogenous shocks, such as the sudden outbreak of the COVID-19 pandemic, whether the utility of information systems can build resilience remains a research gap that may exceed the understanding established in the current IS literature.

To fill this research gap, our study focuses on individual physicians' digital resilience in the online healthcare setting during the first wave of COVID-19 outbreak. COVID-19 is a worldwide exogenous shock that has caused unprecedented challenges to public health systems and global economies (Trang et al. 2020). Given the speed and severity with which the COVID-19 pandemic emerged and spread, there is an urgent need to investigate the role of information systems in the age of the COVID-19 pandemic. Specifically, we focus on a particular healthcare information system—online healthcare communities (OHCs) that serve as both a marketplace matching patients and physicians and a telemedicine system. We aim to examine the effectiveness of such OHCs on increasing physicians' resilient responsiveness to a major exogenous shock (i.e., the first wave of COVID-19 pandemic). In line with existing IS studies, the OHC investigated in this study is an online healthcare platform on which certified physicians can provide medical information (patients can search for physicians on the basis of the information) and interact with patients to provide professional telemedicine services (e.g., paid diagnostics and/or providing prescriptions) (e.g., Liu et al. 2020a; Wang et al. 2020).This study seeks to make the following three major contributions to the IS research on digital resilience.

First, we operationalize and empirically investigate the nuances of what constitutes digital resilience. Resilience is an interdisciplinary concept with various forms in different time periods of a disruption; for example, while entities may need to reduce the probability of a disruption occurring in the pre-disruption period (e.g., Kim et al. 2015; Sanchis et al. 2020), following a disruption, entities need to minimize severe short-term negative consequences and maximize recovery speed (e.g., Davis et al. 2020; Park et al. 2015; Zobel 2011). Therefore, in line with the resilience literature, digital resilience may also take different forms in the context of improving physicians' resilient responsiveness to the COVID-19 pandemic. However, previous studies of digital resilience in the IS field have mainly captured the entities' general perceptions of resilience (e.g., via surveys) in contexts of predictable disruptions (e.g., supply chain disruptions) (e.g., Chen et al. 2019; Park et al. 2015; Pirkkalainen et al. 2019). As such, their operationalization and conclusions may be insufficient to explain digital resilience following a sudden COVID-19 shock.

In this study, we draw upon the literature of resilience (e.g., Kouvelis and Li 2008; Tomlin 2006) and identify two time periods following the first wave of COVID-19 outbreak. We empirically examine physicians' use of an OHC to achieve a ***resistance effect*** (i.e., to mitigate physicians' caseload reductions) in the *immediate period*, and a ***recovery effect*** (i.e., to facilitate increases in physician caseloads) in the *subsequent period* following a COVID-19 outbreak. That is, we posit that physicians' digital resilience under the exogenous shock of COVID-19 is manifested as our proposed resistance and recovery effects. We theorize that using an OHC enables physicians to acquire new patients and provide telemedicine services, resulting in their resilient responsiveness to the pandemic. We thus postulate and test whether OHCs enable different forms of digital resilience across different time periods following a disruption.

Second, we reveal the underlying mechanisms of digital resilience in the COVID-19 context. While there is emerging research on resistance and recovery trends in the healthcare sector, the analysis is mainly conceptual and based on descriptions of the overall demand and supply of telemedicine services (e.g., Wosik et al. 2020). One econometric challenge involves matching physicians' offline outpatient and online behaviors to identify whether and why physicians' adoption of an OHC leads to digital resilience (e.g., Wang et al. 2020). As such, the underlying mechanisms of digital resilience in the COVID-19 context remain a black box. In this study, we go beyond simply recognizing the effectiveness of OHCs on digital resilience by further investigating the sources of such resilience. In particular, by utilizing two unique datasets collected from the OHC channel and the offline outpatient channel, we posit and empirically examine whether OHCs enable physicians to improve their levels of *new patient acquisition*. New patients in the online channel could mitigate the loss of offline outpatients in the immediate period following a COVID-19 outbreak (i.e., the resistance effect). Furthermore, in the subsequent period, new offline outpatients converting from the online channel could allow physicians' caseloads to rebound to normal levels more quickly (i.e., the recovery effect).

Third, we enrich the understanding of how physicians' effective use of information systems and their online reputation contribute to digital resilience. Current IS studies have concluded that the adoption of information systems can build digital resilience in general (e.g., Chen et al. 2019; Park et al. 2015). However, the best way to apply OHCs to obtain higher resilience remains unclear. For example, there are over 828,000 registered physicians using haodf.com (one of the largest OHCs in China),[3] but it is unlikely that all physicians express the same degree of digital resilience because physicians have different levels of using OHCs. We employ sentiment of physicians' online consultations as the indicator of their effective use of the telemedicine technology in OHCs. Our research thus responds to the call to shift the focus of IS research from use to effective use, especially in healthcare contexts (e.g., Burton-Jones and Volkoff 2017; Tong et al. 2017). Moreover, we investigate the impact of physicians' online reputation on their digital resilience. In our research, online reputation is operationalized as the overall rating of physician quality (Gao et

[3] See https://www.haodf.com, accessed in June 2021.

al. 2015; Gray et al. 2015; Li et al. 2019a)—a signal that may attract new patients and thus strengthen digital resilience. Our investigation of the heterogeneity of digital resilience is of great importance because observing variation in the resistance and recovery effects across physicians informs both academic research and IS strategies in the field of healthcare (Floetgen et al. 2021).

To empirically test our theorization, we exploit a natural experiment in a healthcare setting by matching two longitudinal datasets collected from online and offline channels before and after the first wave of the COVID-19 outbreak in China. We apply a difference-in-differences (DID) model and conduct a series of rigorously designed analyses. The empirical results support the proposed resistance and recovery effects as well as the heterogeneous effects of the sentiment of physicians' online consultations and the overall reputation of the physicians in the OHC. In addition to the three aforementioned theoretical contributions, this study extends beyond the boundaries of healthcare research and has implications for the business continuity and disaster recovery literature. We also provide healthcare entities with strategies for resilience that can be used to combat unpredictable disruptions.

The remainder of this paper proceeds as follows. Section 2 reviews the literature related to this research. Section 3 develops the research hypotheses. Section 4 introduces the natural experiment and reports our empirical methodology and results. Finally, Section 5 discusses our findings and offers implications for research and practice.

CHAPTER 2. LITERATURE AND CONCEPTUAL FOUNDATION

2.1 Online Healthcare Communities (OHCs)

In our research context, an online healthcare community is a comprehensive platform on which patients can search for and directly interact with certified physicians and other patients to solve healthcare-related problems (e.g., Goh et al. 2016; Liu et al. 2020a; Wang et al. 2020). Existing research has examined the impacts of two major functions of OHCs on physicians and patients' decisions and behaviors. The first function of OHCs is for the physicians to provide medical information via OHCs and the potential patients can choose their physicians according to such information (Xiao et al. 2014; Yan and Tan 2017). Thus, OHCs act as a marketplace to match physicians and patients. For example, based on the physician information, the patients can search suitable certified physicians for online consultations or outpatient visits (Yang et al. 2015). In the search process, the patients usually read and refer to several informational cues to judge the physicians' service quality, such as the reputation ratings of the physicians on the OHCs (Gray et al. 2015; Wu and Deng 2019) and the detailed contents of the online consultations between the physicians and other patients (Barrett et al. 2016; Zhang et al. 2019).

The second function of OHCs is for the certified physicians to provide professional telemedicine services (e.g., Liu et al. 2020a; Wang et al. 2020). For example, the physicians can conduct online consultations in which the patients receive diagnostics and prescriptions (Cao et al. 2017). Patients can consult physicians anytime and anywhere via OHCs. Existing research has examined patient satisfaction with online consultations (e.g., Liu et al. 2020b; Tan and Yan 2020) and the postive impacts of physicians' participation in OHCs on patient well-being and patient-physician relationships (Liu et al. 2020a).

Previous studies mainly examine the effects of OHCs on physician outpatient production and performance in the “normal age”. For example, a number of studies suggested that OHCs can lead to more equal relationships between patients and healthcare professionals since OHCs effectively reduce the information gap between patients and physicians (e.g., Bartlett and Coulson 2011; Oh and Lee 2012). As such, patients are more willing to engage in offline medical care. Other studies revealed that OHCs may impair the relationship between patients and physicians because OHCs can cause patients to challenge physicians’ medical authority (e.g., Broom 2005; Jarvenpaa and Majchrzak 2010), leading to suboptimal patient-physician interactions and thus decreases patients’ intentions to engage in offline medical care (Rupert et al. 2014). In the current study, we focus on a different context—the digital resilience of physicians who adopted OHCs to acquire patients and conduct telemedicine services after the pandemic outbreak.

2.2 Digital Resilience

Digital resilience is generally defined as the designing, deploying, and using information systems to prevent, resist, and recover from disruptions (Bakshi and Kleindorfer 2009; Davis et al. 2020). Building resilience to cope with the risks or consequences of disruptions has been an important theme in the literature from various fields, including organization behavior, operations management, and information systems. Existing literature classifies organizational/ supply chain resilience into three major forms, namely, *prevention*, *resistance*, and *recovery*—in both the pre- and post-disruption periods (e.g., Bakshi and Kleindorfer 2009; Davis et al. 2020).

Prevention focuses on the pre-disruption period and refers to an entity’s ability to reduce the probability of the (re-)occurrence of a disruption (Bakshi and Kleindorfer 2009; Wein et al. 2006). This form of resilience emphasizes that having noticed the possibility of the occurrence of a disruption, entities proactively develop strategies to minimize such possibility (Paton and Johnston

2001). Current digital resilience research in the IS field has devoted significant attention to this form of resilience. For example, given the high risk of medical data theft, many healthcare entities take precautions against data breaches by proactively making security investment on antivirus and encryption technologies (Kwon and Johnson 2014).

By contrast, resistance and recovery occur in the post-disruption period. Resistance involves the entities' ability to minimize the initial loss caused by a disruption (Bakshi and Kleindorfer 2009; Ivanov and Dolgui 2019). When a disruption occurs, the entities immediately experience a reduction in performance after the disruption; a low level of this reduction in performance is considered to be an indicator of high resistance (Munoz and Dunbar 2015). Recovery is the attempt to minimize the amount of time the entities take to return to normal levels of performance (Bakshi and Kleindorfer 2009; Bennis 2013). This form of resilience highlights the entities' ability to rebound from adversity after a relatively shorter time period following a disruption (Cohen and Kouvelis 2020). For example, Japanese companies that had multiple suppliers (a typical resilient strategy of supply chain management) recovered their production more quickly after the massive 2011 earthquake (Ambulkar et al. 2015; Olcott and Oliver 2014).

Each form of digital resilience has a distinct temporal focus. Prevention emphasizes the strategies that entities use to deal with predictive disruptions in the pre-disruption period; resistance highlights the minimization of the initial loss immediately following the occurrence of a disruption (i.e., in the immediate period); and recovery focuses on the entities' performance following a disruption after some time has passed (i.e., in the subsequent period).

This study adopts the above categorization of resilience. Given the unpredictable and unprecedented nature of a disruption such as the first wave COVID-19 pandemic, prevention is not applicable in our research context. Therefore, we focus on the post-disruption period and address the resistance and recovery effects of individual physicians in this study. Specifically, we follow the extant literature and distinguish two major time periods in the aftermath of the COVID-19 outbreak, namely, *the immediate period* and *the subsequent period* (e.g., Bakshi and Kleindorfer 2009; Gupta et al. 2016; Yan and Martinez 2017). The key characteristic of the immediate period following a disaster or disruption is that people and/or organizations suffer great losses in production and lack sufficient knowledge about the disaster or disruption (Pan et al. 2020). In the subsequent period following a disaster or disruption, the affected entities take actions to compensate for losses caused by the disruption and restore their production to normal levels (Gupta et al. 2016). Accordingly, in the current research context, resistance is reflected by the extent to which a physician uses an OHC to mitigate the production damage caused by the pandemic (e.g., reduction in outpatient visits); and recovery is indicated by the extent to which the physician uses the OHC to enable the rapid resumption of his/her healthcare services.

CHAPTER 3. HYPOTHESIS DEVELOPMENT

We investigate the effects of physicians' use of digital technologies to improve their resilient responsiveness across different time periods following disruptions. In particular, we contextualize digital resilience as enabled by OHCs in *the first wave of the COVID-19 outbreak*. As we focus on the impacts of OHCs on digital resilience, we distinguish two types of physicians, namely, *OHC* and *non-OHC physicians*. OHC physicians refer to those who not only provide offline services in hospitals but also participate in OHCs to provide telemedicine services (i.e., online consultations). Non-OHC physicians refer to those who do not participate in OHCs and provide offline services *only*. We articulate that digital resilience is constituted by a resistance effect in the immediate period and a recovery effect in the subsequent period following the COVID-19 outbreak. Specifically, a resistance effect is referred to as the physicians having less reduction in their production and a recovery effect is referred to as the physicians having greater increase in their production. In the following we develop the hypotheses for these two effects of digital resilience and the heterogeneity of the two effects by considering two moderators (i.e., the sentiment of physicians' online consultations and the physicians' reputation on the OHCs).

3.1 Resistance Effect in the Immediate Period after the COVID-19 Outbreak

In the healthcare settings, a physician's production is often measured by the number of patient consultations that the physician conducts per day/week (e.g., Cayirli and Veral 2003; Salzarulo et al. 2011). These consultations can be resolved via outpatient visits in the hospital or via telemedicine services on OHCs. As COVID-19 is a major exogenous shock to physicians' production, we theorize physicians' resilient responsiveness toward the COVID-19 outbreak by comparing the number of consultations of OHC versus non-OHC physicians before and after the outbreak. While the COVID-19 outbreak has an exogenous negative influence on the number of offline consultations performed by both OHC and non-OHC physicians, we argue that in the immediate period after the outbreak, the magnitude of this influence differs between OHC and non-OHC physicians. Specifically, we posit that the reduction in the number of consultations performed by OHC physicians is lower than that of non-OHC physician because OHC physicians can achieve digital resilience by readily utilizing the OHCs to compensate for the loss of their offline production, whereas non-OHC physicians cannot. This is the resistance effect for the OHC physicians in the immediate period after the outbreak.

In the immediate period after the first wave of the COVID-19 outbreak, physicians face difficulties in conducting offline consultations due to social distancing (some cities may have lockdown policies) and patients' avoidance of offline visits to minimize the risk of infection (Waizenegger et al. 2020). In addition, the healthcare system is unprepared and inexperienced for such a shock, thus suffering a disruption in the supply of offline healthcare services (Sakurai and Chughtai 2020). Thus, although many patients need medical care at that time, emerging barriers challenge them from seeking offline consultations, resulting in a significant reduction of all physicians' offline production.

The Internet in general and clouding computing in particular are robust under external disruptions such as the COVID-19 outbreak, because the OHCs built upon the digital infrastructure are technically reliable for telemedicine services (Hollander and Carr 2020). Thus, immediately after the COVID-19 outbreak, these OHCs are accessible for both physicians and patients anytime and anywhere (Liu et al. 2020a). Different from non-OHC physicians, OHC physicians are able to utilize OHCs to continue their production in the immediate period in two ways. First, existing patients on OHCs, i.e., those who had online consultations with the OHC physicians before the pandemic, can continue seeking the physicians' telemedicine services after the outbreak. Second, OHC physicians can acquire new patients on the OHCs. Specifically, these new patients are categorized into the following two types: (1) <u>new online patients who are transferred from the offline channel</u>: patients who visited an OHC physician on outpatient can continue seeking medical advice from the same physician via online consultations; and (2) <u>totally new online patients</u>: patients who utilize OHCs as a marketplace to search for and find an OHC physician for telemedicine service. For new patients transferred from the offline channel, they have interacted with and are familiar with the OHC physician in the outpatient channel. Therefore, when these patients need online consultations, they will probably seek advice from the same physician (Cao et al. 2017; Liu and Chan 2011). The totally new patients, on the other hand, are those who need online consultations but have not met the physician before. They search on OHCs and select a physician based on the information about the physician's profile and past records of telemedicine services with other patients (Li et al. 2019b; Yang et al. 2015).

We postulate that new patient acquisition discussed above is the major source of OHC physicians' resistance in the immediate period after the COVID-19 outbreak, because they can replace their offline outpatient visits with online consultations. By contrast, in such a short period of time, non-OHC physicians would have been less prepared or unable to immediately switch to the online channel. OHCs provide a reliable venue for existing and new patients to obtain medical diagnosis from the targeted physicians without the risk of COVID-19 infection. In short, in the immediate period after the outbreak, OHC physicians can conduct medical consultations online, resisting the production loss caused by the disruption. Therefore, we hypothesize:

H1 (Resistance Effect): *In the immediate period after the COVID-19 outbreak, the magnitude of the reduction in the consultations provided by the OHC physicians is lower than that of the non-OHC physicians.*

3.2 Recovery Effect in the Subsequent Period after the COVID-19 Outbreak

In the subsequent period after a disruption, the affected entities need to take actions to restore their production to normal levels (Gupta et al. 2016). In the context of COVID-19, the offline outpatient channel is less constrained and gradually restored in the subsequent period (Fahey and Hino 2020). While the logic of acquiring existing and new online patients for OHC physicians is also valid in the subsequent period and these online patients constitute one source of OHC physicians' recovery, the recovery effect in the subsequent period is more on offline consultations, which is different from the resistance effect in the immediate period. Still, we expect a greater magnitude of recovery of OHC physicians than that of non-OHC physicians due to the positive effects of OHCs on physicians' restoration of offline production.

In the subsequent period, the existing offline patients (i.e., patients who had *only* offline consultations with their physicians on outpatient before) start returning to hospitals for outpatient visits. This stream of patients contributes to the source of recovery for both OHC and non-OHC physicians. However, OHC physicians have another additional component in this stream—those who switched from offline to online in the immediate period after the outbreak may return to the offline channel. More importantly, we assert that OHC physicians can also acquire more new offline patients than non-OHC physicians, because OHCs can contribute to the acquisition of two types of new offline patients: (1) new offline patients who are transferred from the online channel: patients who visited the physician on OHCs but have not visited the physician offline; and (2) totally new offline patients who have searched OHCs: patients who have neither visited the physician offline nor consulted the physician via OHCs before.

Regarding new offline patients that are transferred from the online channel, during the immediate period after the outbreak, these patients have kept in touch with the physicians on OHCs. Specifically, patients' interactions with physicians on OHCs contain personal and contextual details (e.g., patients can describe their symptoms), which help the physicians as well as the patients to concretely evaluate the progression of symptoms and decide whether the patients need to receive additional offline treatments (Li et al. 2016; Yan et al. 2019). Therefore, OHC physicians can acquire new offline patients from online consultations by calling for patients' outpatient visits when the physicians consider that the patients need further treatments or examinations. As for the totally new patients, experiencing the disruption of the offline healthcare system, many patients become accustomed to searching information about physicians on OHCs before deciding to make an outpatient visit (Gong et al. 2021; Yuan and Deng forthcoming). The patients can refer to information about the physicians, such as judging whether the physician matches the patient's current health condition and whether the physician is available in outpatient (e.g., Li et al. 2019b; Maloney-Krichmar and Preece 2005; Wang et al. 2018; Yang et al. 2015).

In sum, given the above positive impacts of OHCs on offline patient acquisition in the subsequent period after the COVID-19 outbreak, OHC physicians' production can bounce back with greater magnitude (i.e., restore to the normal-level production more quickly) than non-OHC physicians, who are unable to benefit from OHCs but heavily rely on the existing patients. Therefore, we hypothesize:

H2 (Recovery Effect): *In the subsequent period after the COVID-19 outbreak, the magnitude of the increase in the consultations provided by OHC physicians will be higher than that of non-OHC physicians.*

3.3 The Moderating Roles of Sentiment and Reputation

We further develop the hypotheses regarding the heterogeneity of digital resilience in this section. Effective use of information systems can produce better performance (Burton-Jones and Grange 2013). In the OHC context, it is unlikely that all physicians have the same level of use of OHCs. Therefore, investigating how physicians' use of OHCs affect their digital resilience is necessary (Burton-Jones and Volkoff 2017; Tong et al. 2017). In this study, we employ the sentiment of physicians' online consultations as the indicator of their effective use of the telemedicine system on OHCs.

The sentiment of a physician's online consultations refers to the extent to which the communications between the physician and patients are in a positive direction; it reflects whether the physician effectively uses OHCs to maintain good relationships with his/her patients (e.g., Homburg et al. 2015; Lu et al. 2017). We argue that physicians with more positive online consultations will have stronger digital resilience. As discussed above, in the immediate period after the COVID-19 outbreak, the resistance effect is based on new online patients (both totally new online patients and those who switch from the offline channel). New patients searching for physicians on OHCs may read and refer to the details of online consultations, especially those addressing symptoms similar to theirs, to select a physician for telemedicine service (Gray et al. 2015; Yan et al. 2019). Extant research has shown that customers prefer vendors who maintain good relationship with the customers (in our context physicians with positive sentiment of their online consultations) (e.g., Gefen and Ridings 2002; Stuchfield and Weber 1992). Therefore, new patients are more likely to consult a physician with more positive online consultations, which in turn leads to a stronger resistance effect.

In the subsequent period after the COVID-19 outbreak, if a physician has maintained good relationships with his/her online patients, the latter will be more likely to visit this physician when they need further offline medical care—these patients are the new offline patients who are transferred from the online channel. The totally new offline patients who search on OHCs and refer to the details of physicians' online consultations will also be more likely to select a physician with more positive online consultations, resulting in a stronger recovery effect. Therefore, we hypothesize:

H3a: *The resistance effect in the context of the COVID-19 pandemic is stronger for OHC physicians with greater positivity of online consultations.*

H3b: *The recovery effect in the context of the COVID-19 pandemic is stronger for OHC physicians with greater positivity of online consultations.*

We also investigate the impact of physicians' online reputation on their digital resilience. We argue that high online reputation may attract new patients and thus strengthen digital resilience. In general, a physician's overall reputation rating is a strong and reliable signal of his/her service quality (e.g., Bolton et al. 2004; Gao et al. 2015; Ye et al. 2014). This is because building high reputation is difficult for an OHC physician (Guo et al. 2017). It requires an OHC physician's long-term investment of time and effort to provide various high quality services (e.g., Lin et al. 2018; Liu et al. 2020a). The reputation of OHC physicians is especially important for totally new patients in both the immediate period and the subsequent period. This is because these patients are not familiar with OHC physicians and often seek cues/signals such as online reputation ratings as a key criterion of selecting physicians (Gao et al. 2015). In the immediate period, totally new online patients tend to choose high-reputation OHC physicians for online consultations. In the subsequent period, totally new patients who search on OHCs will rely on the same signal but for offline consultations. Therefore, we argue that physicians with high overall reputation attain stronger resistance and recovery effects. In sum, we hypothesize:

H4a: *The resistance effect in the context of the COVID-19 pandemic is stronger for OHC physicians with high (vs. low) reputation on the OHC.*

H4b: *The recovery effect in the context of the COVID-19 pandemic is stronger for OHC physicians with high (vs. low) reputation on the OHC.*

CHAPTER 4. EMPIRICAL METHODOLOGY AND RESULTS

4.1 Empirical Context and Data

To test our hypotheses, we matched two comprehensive datasets (one online and the other offline) and further analyzed the merged dataset using the event window of 13 weeks before and after the first wave of the COVID-19 outbreak in China. The COVID-19 outbreak in China enabled a natural experiment to test the hypotheses. We exploited the COVID-19 outbreak as the exogenous shock that created plausible variations in online and offline healthcare consultation behaviors among physicians and patients. We analyzed the resistance and recovery effects of OHC physicians compared with non-OHC physicians in the respective immediate and subsequent periods following the outbreak.

The Immediate Period and the Subsequent Period

To generate credible causal evidence for our hypotheses, we exploited two events in order to divide the time period after the first outbreak of COVID-19 into the immediate and subsequent periods so that we could analyze the resistance and recovery effects, respectively. **The first event was the first COVID-19 outbreak.** On January 20, 2020, the Chinese government announced that the coronavirus can spread among human beings and suggested practicing social distancing in order to prevent the spread of COVID-19. On January 23, 2020, the Chinese government officially locked down Wuhan and several other cities in Hubei province. We consider these two official announcements of COVID-19 to be signals of the COVID-19 outbreak. Following these two announcements, many cities in China began to enforce self-isolation, social distancing, and (partial) lockdown measures to prevent the spread of COVID-19. Thus, we designate the COVID-19 outbreak as beginning on January 20, 2020 in our analysis, with the immediate period beginning on this day and lasting until the second event, which occurred on February 23, 2020.

The second event was the announcement of the resumption of people's lives and work activities. On February 23, 2020, the Chinese government announced that work could resume, which signaled that the spread of COVID-19 was under control. People's lives and work activities began to return to normal, as did the healthcare system. Thus, for our purpose, the second event occurred on February 23, 2020. We designate the time period between the first and second event as the immediate period, and the time period after the second event as the subsequent period.

The Offline and Online Datasets

We collected our offline and online data of physicians of a leading hospital located in a city of northern China (Hospital A hereafter).[4] The offline dataset includes the outpatient consultation records from Hospital A. These records are generated from traditional medical consultations where

[4] In our research context, the pandemic situation in the focal city was not as serious as that in Wuhan. While the local city government did not implement formal lockdown and the focal hospital did not implement any no-acceptance policy regarding non-critical outpatients/inpatients, the local government did follow the central government's announcements and instructions to 1) discourage citizens from outdoor activities in the immediate period and 2) encourage citizens to resume the normal life and work in the subsequent period.

the patients go to Hospital A to consult with a physician and obtain prescriptions or medical treatments. The data includes offline outpatient consultations from all physicians (OHC and non-OHC physicians), together with the physicians' profiles in Hospital A. This dataset thus consists of a time series of offline consultations of both OHC and non-OHC physicians. Specifically, for each offline consultation record, we have the physician's information, the date and time of the consultation, and the primary diagnosis identified by International Classification of Diseases, Tenth Revision, Clinical Modification (ICD hereafter) codes. The ICD coding system provides a global standard for diagnostic classification;[5] for example, code number "K40" represents the diagnosis of "inguinal hernia" (Catena et al. 2020). The ICD codes are widely adopted in the healthcare management studies to control for patient heterogeneity and physician specialization (e.g., Anderson et al. 2014; Bartel et al. 2020; Wani et al. 2020). This method is followed because the ICD codes can reflect the patients' medical conditions (e.g., the diseases and symptoms) which are the primary motivation for patients to visit a specific physician in the hospital (Clark and Huckman 2012; Kuntz et al. 2019). Therefore, in this study, we also apply ICD codes to control for the patient heterogeneity and physician specialization.

The online dataset was collected from a Chinese online healthcare community (OHC) platform—haodf.com. This platform was established in 2006 and currently represents one of the largest OHCs in China. The haodf.com has been widely adopted as the empirical context for previous OHC studies in the IS field (e.g., Guo et al. 2017; Liu et al. 2020a; Wang et al. 2020). As of June 2021, more than 834,000 certified physicians from 9,718 hospitals across the country had registered with the platform.[6] The platform maintains a homepage for each certified physician

[5] The Centers for Disease Control and Prevention (2021) provides a detailed description of the ICD system (see https://www.cdc.gov/nchs/icd/icd10cm.htm#FY%202021%20release%20of%20ICD-10-CM, accessed in June 2021).
[6] See https://www.haodf.com, accessed in June 2021.

including biographical, professional, reputation rating, and contents of their online consultations. Patients can utilize such information to target physicians for paid consultations. The platform thus enables the certified physicians to present profile information on their homepages and provide professional telemedicine services. For the telemedicine services (i.e., online consultations), physicians can directly communicate with patients on the platform. Figure 1 depicts the screenshots of a physician's homepage and his/her online consultations on the OHC.

As of June 2020, among the 912 physicians of Hospital A, 248 physicians had registered as users on the OHC platform.[7] Physicians mainly use the OHC to providing online consultations (i.e., the telemedicine service). These online consultations are paid services that involve formal one-to-one communications between patients and physicians and these communications are publicly accessible (Wang et al. 2020). We collected data about physicians' online consultations as a time series and their information on the homepage (e.g., the reputation ratings). We also identify the ICD code for each online consultation in accordance with the diagnosis information of the consultation (see Figure 1 on next page). This process is under the proper supervision of professional physicians and the reference of guidelines for the ICD system. The online dataset thus consists of a time series of online consultations of OHC physicians from Hospital A. After data desensitization, we matched the offline dataset with the online dataset by each OHC physician to investigate the physicians' online and offline behaviors at the individual level.

[7] We have interviewed the senior management and the OHC physicians of Hospital A. They pointed out that 1) Hospital A had not implemented its own telemedicine system; and 2) the OHC physicians did not provided telemedicine services on other OHC platforms than haodf.com.

Figure 1. Screenshot of a Physician's OHC Homepage and Online Consultation

4.2 Empirical Strategy

We implemented a difference-in-differences (DID) model to examine the resistance and recovery effects. For the resistance effect, we ran the DID model using the data in the immediate period after the COVID-19 outbreak and its parallel period before the outbreak. For the recovery effect, we ran the DID model using the data in the subsequent period after the COVID-19 outbreak and its parallel period before the outbreak. Figure 2 presents the timeline of our analysis. We then explored the heterogeneity of the treatment effects using the *sentiment of physicians' online consultations* and *physicians' overall reputation on the OHC* as two moderators.

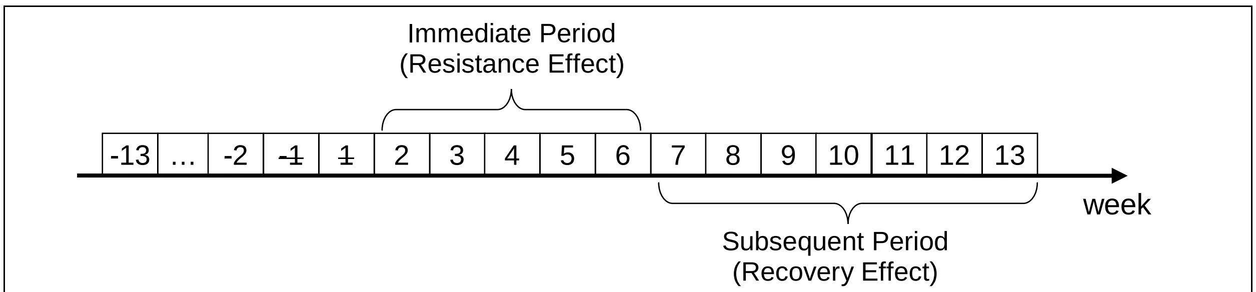

Figure 2. Timeline of the Analysis

The unit of time window is one week and our data contain a total of 26 weeks (13 weeks pre- and 13 weeks post-outbreak day). The weeks were marked from -13 to 13 without 0. We eliminated one week pre- and post-outbreak time point (January 20, 2020) from our analysis, as the two weeks are considered to be the reference periods. The signal day of recovery (i.e. the second event) is between Week 5 and Week 6 in our data hence the immediate period is represented from Week 2 to Week 6 and the subsequent period is represented from Week 7 to Week 13. Specifically, we tested the resistance effect using the dataset from Week -6 to Week -2 as the pre-treatment period and the dataset from Week 2 to Week 6 as the post-treatment period (i.e., the immediate period). We also tested the recovery effect using the dataset from Week -13 to Week -7 as the pre-treatment period and the dataset from Week 7 to Week 13 as the post-treatment period (i.e., the subsequent period).

4.3 Variables

The unit of the analysis is each physician (OHC vs. non-OHC physicians). The productions of physicians are operationalized as consultations provided by the physician, including offline consultations (for OHC and non-OHC physicians) and online consultations (only for OHC physicians).[8] We define $Total\_consultation_{it}$ as the number of consultations provided by physician i in week t. For OHC physicians, this number is the sum of their online and offline consultations. For non-OHC physicians, this number equals the number of offline consultations as non-OHC physicians provide offline consultations only. Offline consultations are the total number of outpatient visits of physician i in week t, denoted as $Offline\_consultation_{it}$. We operationalized $Online\_consultation_{it}$ on the basis of the total number of OHC physicians' online consultation of physician i in week t. The binary variable $OHC\_physician_i$ indicates whether physician i had registered with the OHC or not (1 means physician i is an OHC user and 0 means physician i is not an OHC user). The outbreak of COVID-19 was operationalized as a binary variable $outbreak_t$ with 1 indicating after the outbreak and 0 before the outbreak.

We also included several physician-level variables and COVID-19 statistics variables as controls, including the physician's ICD codes, title, educational level, work experience, age, and gender. Specifically, for a physician's ICD codes, in line with previous studies (e.g., Anderson et al. 2014; Bartel et al. 2020; Wani et al. 2020), we generate ICD code vectors by considering all the individual cases during the time window of our study (if a physician had one consultation case

[8] We have conducted interviews with both the senior management of Hospital A and the physicians in our sample and all indicated that multiple affiliations are not allowed in Hospital A. Thus, the number of consultations of a physician in Hospital A sufficiently captures his/her production. Similarly, all OHC physicians in our sample only use the focal OHC for telemedicine services. The number of consultations on the OHC thus sufficiently captures their online production.

with a certain 3-digits ICD code, we set this ICD code dummy to 1, and 0 otherwise). In our dataset, there are 792 dimensions for each ICD code vector. The statistics of COVID-19 contain new cases, cured cases, and death cases per week of the local province where Hospital A is located (there is no official report of the cases of the focal city). Table 1 presents the list of variables and measures.

Table 1. Variables and Measures

Variable	***Measure***	***Data Source***
$Total\_consultation_{it}$	Sum of $Offline\_consultation_{it}$ and/or $Online\_consultation_{it}$ representing physician *i*'s consultations in week *t*	Physician *i*'s OHC page and Hospital A
$Online\_consultation_{it}$	The total number of physician *i*'s online consultations in week *t*	Physician *i*'s OHC page
$Offline\_consultation_{it}$	The total number of physician *i*'s outpatient consultations in week *t*	Hospital A
$OHC\_physician_i$	A binary variable that indicates whether physician *i* had registered on the OHC, which takes 1 for OHC physicians, and 0 for non-OHC physicians	Physician *i*'s OHC page
icd_codes_i	A vector that if the physician *i* has a consultation with a certain ICD code, this ICD code dummy takes 1, and 0 otherwise	Physician *i*'s OHC page and Hospital A
$title_i$	The medical title of physician *i*, which takes the value 1 for "attending physician", 2 for "associate chief physician", and 3 for "chief physician"[9]	Hospital A
$education_i$	The educational qualification of physician *i*, which takes 1 for physicians with "Clinical Medicine Postgraduate", and 0 for physicians with lower educational qualification	Hospital A
$experience_i$	Years of work experience of physician *i* by the end of week 13	Hospital A
age_i	Age of physician *i* by the end of week 13	Hospital A
$gender_i$	Gender of physician *i*, which takes 1 for female and 0 for male	Hospital A
new_case_t	Number of new confirmed cases of COVID-19 in the local province in week *t*	Government
$cured\_case_t$	Number of cured cases of COVID-19 in the local province in week *t*	Government
$death\_case_t$	Number of death cases of COVID-19 in the local province in week *t*	Government

4.4 Data Analysis

We first ran DID models in the immediate period and subsequent period, respectively, to analyze

[9] The categorization of $title_i$ is widely adopted in IS research on Chinese OHC (e.g., Li et al. 2021). The empirical results are consistent and robust using two dummies representing the three level of titles.

the resistance and recovery effects of OHC physicians after the COVID-19 outbreak (i.e., H1 and H2). Then, we ran DID models using different subgroups of OHC physicians to analyze how the resistance and recovery effects are moderated by the sentiment of physicians' online consultations (i.e., H3a and H3b) and physicians' overall reputation on the OHC (i.e., H4a and H4b).

Propensity Score Matching

We utilized propensity score matching (PSM) to select OHC physicians as the treatment group and non-OHC physicians as the control group, before running the DID tests (Guo and Fraser 2014; Liu et al. 2020a). To identify a pair of physicians who are similar in terms of observable characteristics, we first ran a logit model to evaluate the possibility that a physician adopts the OHC, in which the following physician-level variables were controlled: the physician's (1) title, (2) age, (3) gender, (4) years of work experience, (5) educational qualification, and (6) ICD codes. The detailed results of the logit regression are summarized in Table A1 in Appendix A. We then matched the OHC physicians and non-OHC physicians using one-one nearest neighbor matching method (Guo and Fraser 2014; Pamuru et al. 2021). After matching, there were 77 OHC physicians and 77 matched non-OHC physicians in our dataset.[10] The descriptive statistics of all the variables after the PSM are reported in Table A2 in Appendix A.

To verify the validity of the matching, we applied paired *t*-tests to compare the five matching variables between the treatment and control groups before and after matching, i.e., the physicians' title, age, gender, years of work experience, and educational qualification. The results indicate no significant differences in these variables between the treatment and control groups. Table 2 reports the summary statistics of the comparisons.

[10] We eliminated the inactive OHC physicians who did not provide any online consultation across the 26 weeks. Also we excluded the OHC physicians who registered the OHC after the COVID-19 outbreak. After the elimination, there were 77 OHC physicians and all of them were matched with non-OHC physicians by PSM.

Table 2. Comparisons of Matching Variables Before and After PSM

Variable		*Mean*		*t-value*
		Treatment (OHC Physicians)	*Control (Non-OHC Physicians)*	
$title_i$	Before	1.89	1.69	1.50
	After	1.89	2.05	-1.07
age_i	Before	43.27	42.42	0.89
	After	43.27	44.87	-1.27
$gender_i$	Before	0.47	0.53	-1.01
	After	0.47	0.46	0.16
$experience_i$	Before	17.88	16.71	0.99
	After	17.88	19.71	-1.15
$education_i$	Before	1.00	1.00	/
	After	1.00	1.00	/

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

For the physicians' ICD codes, to further alleviate the concern of the heterogeneity among different groups of physicians or consultations, we first checked the cross-sectional variation of ICD codes in the entire time period (i.e., from Week -13 to Week 13) between OHC physicians and non-OHC physicians. We then compared the OHC physicians' ICD codes before vs. after the pandemic (i.e., from Week -13 to Week -2 vs. from Week 2 to Week 13, for OHC physicians' ICD codes). We also made comparisons of OHC physicians' online and offline consultations' ICD codes in the entire time period. In particular, we utilized the Hotelling's T^2 tests to examine the potential differences among ICD code vectors (Hotelling 1951; Redinger 2011). Hotelling's T^2 has been widely adopted to check the potential differences between two vectors (e.g., Colin et al. 2015; Wu and Zhang 2006).

Table 3 reports the results of the Hotelling's T^2 tests, which show that the differences are *all* insignificant for *OHC vs non-OHC physicians'* ICD codes, *OHC physicians' ICD codes before vs after the pandemic outbreak*, and *OHC physicians' ICD codes of online vs offline consultations*. And the findings are robust to the 1-digit and 2-digits ICD codes. The results suggest that (1) the OHC physicians and non-OHC physicians were facing similar medical demands from patients; (2) for OHC physicians, the pandemic did not change their patients' demands; and (3) the patients' demands of OHC physicians did not vary across different channels.

Table 3. Results of the ICD Codes Comparisons		
Comparisons	**Hotelling's T^2**	***p*-value**
OHC Physicians' vs. non-OHC Physicians' ICD Codes	0.87	0.623
OHC Physicians' ICD Codes Before vs. After the Pandemic Outbreak	0.54	0.995
OHC Physicians' Online vs. Offline ICD Codes	1.14	0.361
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Estimating the Resistance Effect and Recovery Effect: Differences-in-Differences Analysis

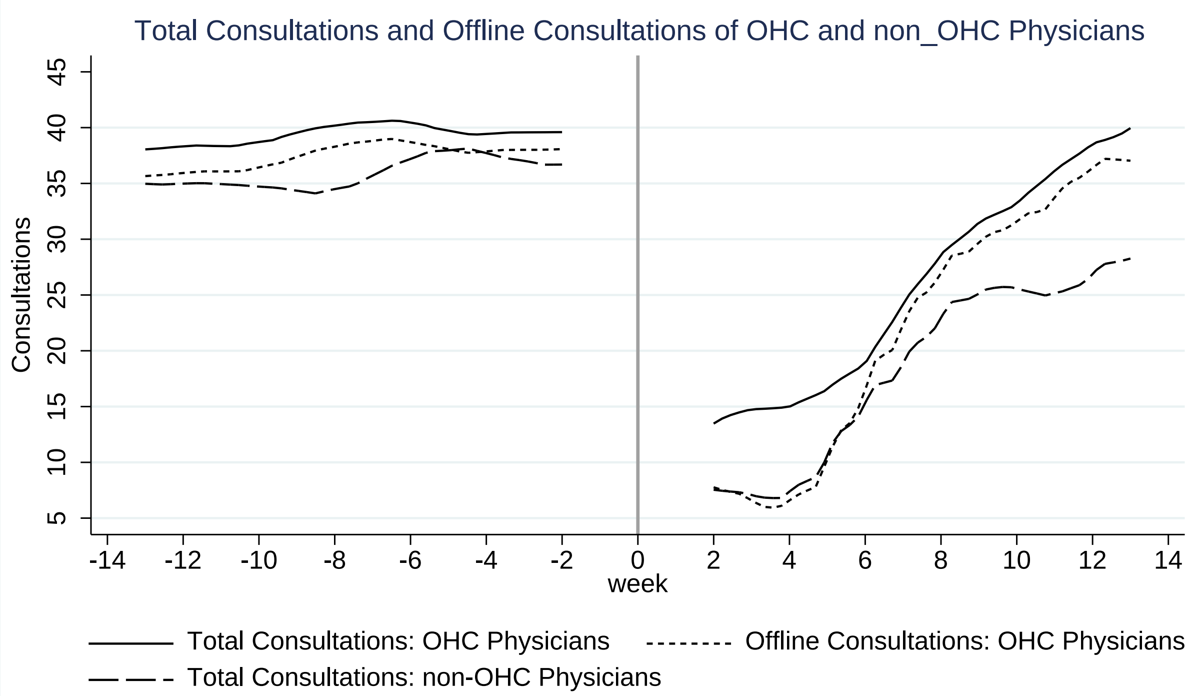

Figure 3. Physicians' Consultations

We plotted the total consultations of OHC physicians and non-OHC physicians and the offline consultations of OHC physicians in Figure 3 above. We can observe that before the COVID-19 outbreak, the productions of OHC physicians and non-OHC physicians were quite stable with small variations in the normal period. However, the COVID-19 outbreak brought a substantial reduction of total consultations and offline consultations to both the OHC and non-OHC physicians in the immediate period (Week 2-6). While there was no significant difference in the magnitude of reduction in offline consultations for OHC vs. non-OHC physicians in the immediate period (the dot line vs. the dash-dot line), there was a significant difference in the magnitude of reduction in total consultations for OHC physicians versus non-OHC physicians (the solid line vs. the dash-dot line). In the subsequent period (Week 7-13), the total consultations and offline consultations gradually increased with OHC physicians' production approaching the levels in the normal period before the outbreak (the solid line and the dot line). However, non-OHC physicians were left behind (the dash-dot line). To provide statistical support for the above model-free evidence, we employed the following DID specifications to examine and quantify the treatment effects:

$$\begin{aligned} total\_consultation_{it} &= \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i \\ &+ \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} offline\_consultation_{it} &= \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i \\ &+ \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

Existing literature suggested that physicians' production/performance follows the power law distribution (e.g., Aguinis and O'Boyle Jr. 2014; Joo et al. 2017) and our data follow the same pattern. Therefore, we applied the natural logarithm transformation to the numbers of physicians' consultations. Specifically, in Equation (1), $total\_consultation_{it}$ is the log of the number of physician *i*'s total consultations in week *t*, i.e., $ln(Total\_consultation_{it}+1)$; and in Equation (2), $offline\_consultation_{it}$ is the log of the number of physician *i*'s offline consultations in week *t*, i.e., $ln(Offline\_consultation_{it}+1)$. **X** contains all the control variables including physician-level variables (i.e., title, age, gender, work experience, and educational qualification) and COVID-19 statistics (i.e., the new cases, cured cases, and death cases per week of the local province). Finally, α_i captures the physician fixed effects and δ_t captures the time fixed effects.

We ran the DID models with the immediate period following the outbreak and its parallel period before the outbreak to verify the resistance effect (from Week -6 to Week -2 and from Week

2 to Week 6). Moreover, we run the DID models with the subsequent period and its parallel period before the outbreak to verify the recovery effect (from Week -13 to Week -7 and from Week 7 to Week 13). The coefficient of $OHC\_physician_i{*}outbreak_t$ (i.e., $\widehat{\beta_1}$) is of interest since $\widehat{\beta_1}$ estimates the percentage changes in the dependent variables (DVs) for OHC physicians (vs. non-OHC physicians) after the COVID-19 outbreak. Therefore, $\widehat{\beta_1}$ captures the effect of COVID-19 on OHC physicians' production relative to non-OHC physicians' production (i.e., the resistance and recovery effects). The results of the DID regressions are reported in Table 4.

Table 4. Resistance and Recovery Effects of OHC Physicians

DV	***total_consultation$_{it}$***						***offline_consultation$_{it}$***					
Time Window	**[-6, -2] & [2, 6] (Resistance)**			**[-13,-7] & [7,13] (Recovery)**			**[-6, -2] & [2, 6] (Resistance)**			**[-13,-7] & [7,13] (Recovery)**		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OHC_physician$_i$ * outbreak$_t$	**0.38*** (0.14)**	**0.38** (0.15)**	**0.38** (0.15)**	**0.26** (0.13)**	**0.26* (0.14)**	**0.26* (0.14)**	**0.19 (0.14)**	**0.19 (0.15)**	**0.19 (0.15)**	**0.28** (0.13)**	**0.28** (0.14)**	**0.28** (0.14)**
OHC_physician$_i$	-0.35 (0.22)	-0.04 (0.15)	0.03 (0.07)	-0.30 (0.22)	-0.93*** (0.09)	-0.88*** (0.07)	-0.42* (0.23)	-0.74*** (0.11)	-0.66*** (0.08)	-0.43* (0.23)	-1.22*** (0.11)	-1.13*** (0.07)
outbreak$_t$	-1.28*** (0.09)	-0.70*** (0.15)	-1.54*** (0.29)	-0.28*** (0.09)	-2.67*** (0.69)	-3.55*** (1.33)	-1.28*** (0.09)	-0.55*** (0.14)	-1.56*** (0.27)	-0.28*** (0.09)	-2.47*** (0.65)	-2.84** (1.27)
Control Variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Physician FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
No. of Physicians	154	154	154	154	154	154	154	154	154	154	154	154
Adj. R-Squared	0.14	0.77	0.77	0.01	0.75	0.76	0.17	0.78	0.78	0.01	0.78	0.79

Note: Standard errors in parentheses are robust and clustered by time and physician.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The empirical results were consistent with our H1 and H2. We assessed the resistance effect of OHC physicians by using data from Week -6 to Week -2 and from Week 2 to Week 6. First, in the immediate period after the COVID-19 outbreak, OHC physicians retain significantly higher total consultations than that of non-OHC physicians (i.e., positive $\widehat{\beta_1}$s in Columns 1-3). In other words, the magnitude of the reduction of OHC physicians' production was lower than that of non-OHC physicians' production. Specifically, $\widehat{\beta_1}$ of Column (3) suggests a 46.2% less reduction in

OHC physicians' total consultations than non-OHC physicians (significant at 1% level).[11] Second, the OHC physicians are not different from non-OHC physicians with regard to offline consultations (i.e., insignificant $\widehat{\beta_1}$s in Columns 7-9). In other words, the outbreak of COVID-19 nearly eliminates the number of offline consultations for both OHC and non-OHC physicians. However, as the OHC physicians are able to utilize the OHC to provide online consultations, the OHC physicians have a stronger resistance compared to non-OHC physicians. Therefore, the resistance effect of OHC physicians is supported by empirical evidence.

We assessed the recovery effect of OHC physicians using data from Week -13 to Week 7 and from Week 7 to Week 13. In the subsequent period after the COVID-19 outbreak, OHC physicians retained significantly higher total consultations (i.e., positive $\widehat{\beta_1}$s in columns 4-6) as well as offline consultations (i.e., positive $\widehat{\beta_1}$s in columns 10-12) than those of non-OHC physicians. In other words, OHC physicians' magnitude of increase in the production is higher than non-OHC physicians. The recovery effect of OHC physicians was significantly positive both for total consultations (Columns 4-6) and offline consultations (Columns 10-12). Specifically, our results reveal that the OHC physicians enjoyed 29.7% more bounce back of total consultations (significant at 10% level, Column 6) and 32.3% more bounce back of offline consultations (significant at 5% level, Column 12) than non-OHC physicians. The recovery effect of OHC physicians is also supported. To conclude, our findings using DID tests are consistent with our observations from the model-free analysis and provide empirical evidence to support H1 and H2.

Validation Tests for DID Analysis

In this section, we report the results of several robustness checks to validate our findings in the DID analysis. First, we ensure that the parallel trends assumption is satisfied for our DVs. That

[11] Given that the DV is in the form of logarithm, the percentage change in the DV is calculated by $e^{\text{coefficient}} - 1$.

is, before the COVID-19 outbreak, OHC physician and non-OHC physicians' consultations followed the similar trends. A visual inspection of Figure 3 reveals the two types of physicians' parallel evolution before the outbreak. In line with previous DID studies, we employed the Augmented Dickey-Fuller test of stationarity to test the parallel trends assumption (e.g., Khern-am-nuai et al. 2018; Pamuru et al. 2021). The results show no pre-treatment differences in the DVs of OHC physicians and non-OHC physicians, leading to the support of the parallel trends assumption (see details in Table B1 in Appendix B).

Second, as the treatment impact may vary given the pandemic progression of COVID-19, we applied the New_case_t (i.e., the log form of the number of new confirmed cases of COVID-19 in the local province in week *t*) as a continuous measure to reflect "treatment intensity." In line with existing studies that use a continuous treatment in DID analysis (e.g., Acemoglu et al. 2004; Hermosilla et al. 2018; Lee et al. 2020), we ran the following DID analysis:

$$DV_{it} = \beta_1 * OHC\_physician_i * outbreak_t * New\_case_t + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \tag{3}$$

where the DV is $total\_consultation_{it}$ or $offline\_consultation_{it}$. As we used the new confirmed COVID-19 cases as the treatment variable, the COVID-19 statistics variables (i.e., the new cases, cured cases, and death cases per week of the local province) were excluded from the **X** in Equation (3). The results are qualitatively similar to those of Equations (1) and (2) (see Table 5), thereby ensuring that our findings are robust to this alternative specification.

Table 5. Treatment Intensity and Digital Resilience				
DV	***total_consultation$_{it}$***		***offline_consultation$_{it}$***	
Time Window	**[-6, -2] & [2, 6] (Resistance)**	**[-13,-7] & [7,13] (Recovery)**	**[-6, -2] & [2, 6] (Resistance)**	**[-13,-7] & [7,13] (Recovery)**
Column	(1)	(2)	(3)	(4)
OHC_physician$_i$ * outbreak$_t$ * New_case$_t$	**0.09*** (0.04)**	**0.14** (0.06)**	**0.04 (0.04)**	**0.14** (0.06)**
OHC_physician$_i$	0.04 (0.07)	-0.81*** (0.02)	-0.65*** (0.07)	-1.05*** (0.02)
outbreak$_t$	-0.75*** (0.10)	0.05 (0.11)	-0.74*** (0.10)	0.06 (0.10)
Control Variables	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of Physicians	154	154	154	154
Adj. R-Squared	0.77	0.76	0.78	0.79

Note: Standard errors in parentheses are robust and clustered by time and physician.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Third, we performed two falsification tests to further establish the robustness of our findings. In the first falsification test, we created a placebo event (Week -6). The results show that this placebo event has no significant effects on the DVs (see Table B2 in Appendix B). In the second falsification test, we examined whether the resistance and recovery effects are artifacts of seasonality. This is because the COVID-19 outbreak event fell in the Chinese New Year week of 2020, which is the most important holiday for Chinese. Thus, one may argue that the observed effects may be caused by such seasonal trend. To rule out such possibility, we examined whether a reduction and bounce back in physicians' production also occurred during the 2019 Chinese New Year. We repeated the same DID analysis using the same physician-level data in 2019 for the same time window in 2020. The results show that this placebo event (Chinese New Year in 2019) has no significant effect on the DVs (see Table B3 in Appendix B).

Fourth, although the official announcement of recovery is made in Week 7, some people may have started their normal work and lives earlier (or later) than that week. Thus, we used Week 6 and Week 8 as thresholds for the subsequent period to rerun the DID models. The results reveal qualitatively similar patterns to our main findings (see Table B4 in Appendix B). In sum, we conclude that our DID analysis generates credible causal evidence.

Moderation Test for Sentiment of Physicians' Online Consultations

Next we examined the moderating effects of the sentiment of physicians' online consultations on the resistance and recovery effects. We collected the detailed physician-patient interactions of all online consultations for each OHC physician (see Figure 1). For each utterance of the physician-patient interactions, we extract the sentiment value embedded in the utterance by applying the deep learning framework of PaddlePaddle (PaddlePaddle 2021). This framework is provided by BAIDU with high accuracy of prediction and has been widely adopted in the sentiment analysis of Chinese texts (e.g., Tang et al. 2020; Xie et al. 2020; Zhou et al. 2020). The sentiment value of an utterance ranges from 0 to 1 indicating the probability that an utterance is of positive sentiment—the higher the value, the greater probability of positivity. In line with existing IS literature (e.g., Yan and Tan 2014; Yan et al. 2019), we then calculated a variable, $sentiment_i$, by summarizing the probability of positive sentiment embedded in the online consultations for physician *i* in the whole time period. Thus, an OHC physicians' $sentiment_i$ describes the likelihood that the OHC physician generally maintains a good relationship with his/her patients. Table A2 in Appendix A shows the descriptive statistics of $sentiment_i$.

We examined whether the resistance and recovery effects for OHC physicians varied according to the sentiment of physicians' online consultations. We first divided the OHC physicians (and thus their matched non-OHC physicians) into two subgroups based on the median of $sentiment_i$, i.e., high vs. low positivity groups. We then repeated the DID analysis with each subgroup and compared the results from these two subgroups.

Table 6 reports the heterogeneity treatment effects of the sentiment of physicians' online consultations. In the immediate period, the $\widehat{\beta_1}$ of total consultations is significant only for OHC physicians with high positivity, but not for OHC physicians with low positivity (Columns 1 and

2). In contrast, we found that the $\widehat{\beta_1}$s of offline consultations are insignificant for both high and low positivity groups (Columns 5 and 6). In other words, for an OHC physician to obtain a resistance effect, he/she needed to be more positive in his/her online consultations with patients. These findings provide the evidence that the resistance effect is moderated by the sentiment of physicians' online consultations, thereby supporting H3a. Similarly, in the subsequent period, we can observe that the $\widehat{\beta_1}$s of both total and offline consultations are significant only for OHC physicians with high positivity (Columns 3, 4, 7, and 8). The results reveal that the recovery effect is moderated by the sentiment of physicians' online consultations and only the physicians with high positivity could enjoy the effect. Thus, H3b is well supported.

Table 6. Impacts of Sentiment on Digital Resilience

DV	***total_consultation$_{it}$***				***offline_consultation$_{it}$***			
Time Window	**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**		**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**	
Positivity	High	Low	High	Low	High	Low	High	Low
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OHC_physician$_i$ * outbreak$_t$	**0.51** **(0.22)**	**0.25** **(0.20)**	**0.34*** **(0.18)**	**0.19** **(0.21)**	**0.33** **(0.21)**	**0.05** **(0.22)**	**0.40**** **(0.17)**	**0.17** **(0.22)**
OHC_physician$_i$	-2.76*** (0.11)	1.96*** (0.10)	-2.21*** (0.09)	2.75*** (0.10)	-2.69*** (0.10)	2.06*** (0.11)	-2.24*** (0.08)	2.76*** (0.11)
outbreak$_t$	-0.95*** (0.15)	-0.71*** (0.18)	-0.19 (0.16)	0.02 (0.18)	-0.89*** (0.15)	-0.68*** (0.18)	-0.19 (0.15)	0.03 (0.18)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Physicians	76	78	76	78	76	78	76	78
Adj. R-Squared	0.80	0.73	0.79	0.72	0.83	0.74	0.84	0.73

Note: Standard errors in parentheses are robust and clustered by time and physician.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Moderation Test for Physicians' Reputation on the OHC

To verify the moderating role of physicians' reputation on digital resilience, we first generated a variable $reputation_i$, which is measured by physician i's overall reputation rating on his/her OHC homepage (see Figure 1). We adopted an approach similar to the previous section to divide OHC physicians (and the matched non-OHC physicians) into high vs. low reputation groups by the median of $reputation_i$. We then repeated the DID analysis with each subgroup and compared the results from these two subgroups.

Table 7 reports the heterogeneity treatment effects of physicians' reputation for both the resistance effect (Columns 1–2 and Columns 5–6) and recovery effect (Columns 3–4 and Columns 7–8) of OHC physicians. In the immediate period, the resistance effects on both total and offline consultations were only significant for physicians with high reputation. Similar results were found with the recovery effects in the subsequent period. The findings thus support H4a and H4b.

Table 7. Impacts of Reputation on Digital Resilience

DV	***total_consultation$_{it}$***				***offline_consultation$_{it}$***			
Time Window	**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**		**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**	
Reputation	high	low	high	low	high	low	high	low
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OHC_physician$_i$ * outbreak$_t$	**0.55*** (0.19)**	**0.16 (0.23)**	**0.56*** (0.19)**	**-0.11 (0.19)**	**0.55*** (0.19)**	**-0.27 (0.23)**	**0.59*** (0.18)**	**-0.12 (0.20)**
OHC_physician$_i$	-0.27*** (0.09)	-3.70*** (0.12)	-0.08 (0.09)	-4.27*** (0.10)	-0.29*** (0.10)	-3.59*** (0.12)	-0.10 (0.09)	-4.26*** (0.10)
outbreak$_t$	-0.95*** (0.18)	-0.68*** (0.15)	-0.23 (0.17)	0.10 (0.18)	-0.96*** (0.18)	-0.55*** (0.13)	-0.20 (0.16)	0.08 (0.17)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Physicians	86	68	86	68	86	68	86	68
Adj. R-Squared	0.78	0.75	0.73	0.79	0.78	0.80	0.76	0.82

Note: Standard errors in parentheses are robust and clustered by time and physician.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Post Hoc Analyses for the Mechanisms of New Patient Acquisition

Utilizing the uniqueness and richness of the matched offline and online datasets, we further explored the new-patient-acquisition mechanism and report the corresponding empirical evidence in this section.

We first identified different types of online patients. For each online consultation on a physician's OHC page, we could observe whether this was the first record of the patient's online consultation with the physician (see Figure 1: the box highlighted with the annotation "The patient's 1st record of online consultation with the physician"). If yes, this patient was identified as a new patient (otherwise an existing patient). We then further classified this new online patient as transferred from the offline channel or totally new. For a new online patient, the online consultation page also recorded whether the patient had seen the physician on offline outpatient before (see Figure 1: the box highlighted with the annotation "Indicating whether the patient has seen the physician on offline outpatient before"). If yes, this new patient was identified as transferred from the offline channel, otherwise a totally new patient.

With regard to offline patients, the outpatient consultation records from our offline dataset indicated whether the patient had visited the physician before. As such, we could classify an offline patient as a new or existing one. However, we were not able to identify whether a new patient is transferred from the online channel or a totally new one because of the privacy issue. The variables and measures related to new patients are presented in Table 8 and the descriptive statistics of these variables are reported in Table A2 in Appendix A.

Table 8. Variables and Measures related to New Patients

Variable	*Measure*	*Data Source*
New_patient$_{it}$	Sum of *Offline_new_patient$_{it}$* and/or *Online_new_patient$_{it}$*, representing the total number of physician *i*'s new patients in week *t*	Physician *i*'s OHC page and Hospital A
Online_new_patient$_{it}$	Sum of *online_new_from_offline$_{it}$* and *online_totally_new$_{it}$*, representing the number of physician *i*'s new online patients in week *t*	Physician *i*'s OHC page
Offline_new_patient$_{it}$	The number of new offline patients of physician *i* in week *t*	Hospital A
online_new_from_offline$_{it}$	The number of new online patients of physician *i* in week *t* who are transferred from the offline channel	Physician *i*'s OHC page
online_totally_new$_{it}$	The number of totally new online patients of physician *i* in week *t*	Physician *i*'s OHC page

To better articulate the source of OHC physicians' digital resilience, we first plotted the proportions of different types of online patients—i.e., existing online patients, new patients from the offline channel, and totally new patients in Figure 4. In general, the majority of OHC physicians' online patients were new patients. Moreover, the proportion of *online_totally_new* increased after the outbreak and became the major source (close to or over 50%) of OHC physicians' online patients. Thus OHC physicians achieved digital resilience by turning offline patients to the OHC (i.e., *online_new_from_offline*) as well as expanding to new patients that come from the OHC (*online_totally_new*), with the latter playing a more significant role.

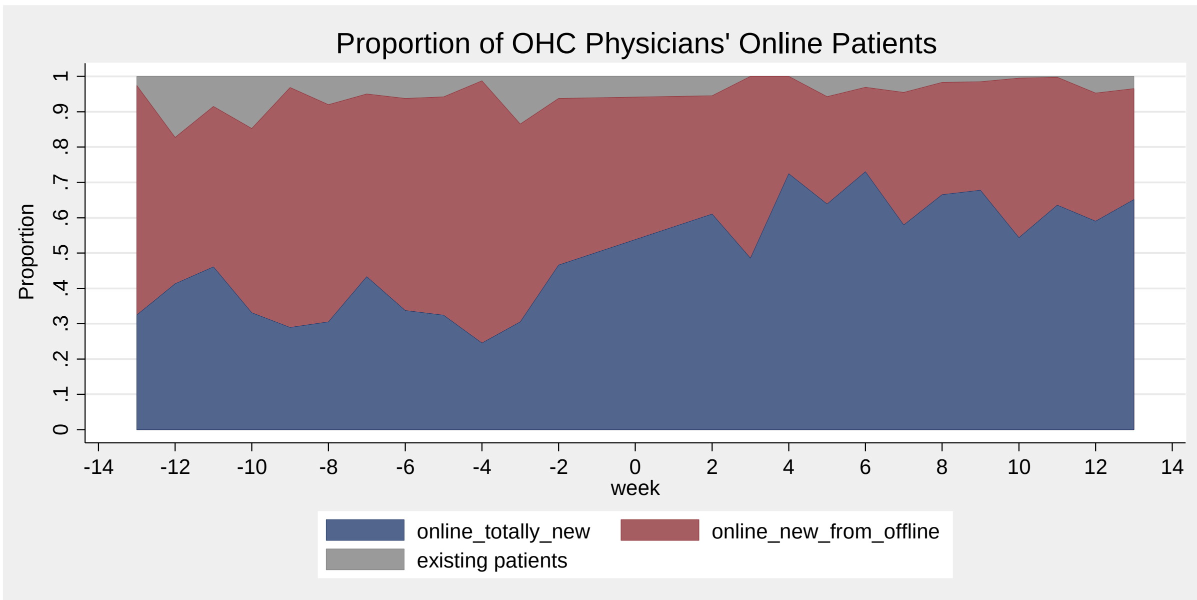

Figure 4. OHC Physicians' Online Patients

For offline patients, as articulated in our Hypotheses Development section, we conjecture that one particular source of OHC physicians' quick bounce back in the recovery period is their calling online patients for offline outpatients. Although we do not have the one-to-one matching between online patients and offline outpatients due to the privacy issue, we provide a side evidence by examining the correlation between *the rate of OHC physicians' online calls for offline outpatients* (i.e., the no. of online calls for offline outpatients[12] over the total no. of online consultations) and *the rate of their offline patients* ($Offline\_consultation_{it}$ divided by $Total\_consultation_{it}$). We found an insignificant correlation between the two before the outbreak (*corr.* = 0.06, $p > 0.1$) and significant correlations in both the resistance (*corr.* = 0.69, $p < 0.1$) and

[12] A research assistant and two of the coauthors read and coded all the online consultations. An online consultation is labeled "online call for offline outpatient" if the physician explicitly asked the patient to visit him/her in hospital for further examinations or treatments (e.g., "please come to the hospital tomorrow afternoon at around 3 pm").

the recovery (*corr.* = 0.81, $p < 0.1$) periods. These findings serve as a side evidence that a particular source of the recovery effect of OHC physicians was transferring their online patients to offline outpatients. Figure 5 below depicts the covariation between the rate of online calls for offline outpatients and the rate of offline patients of OHC physicians.

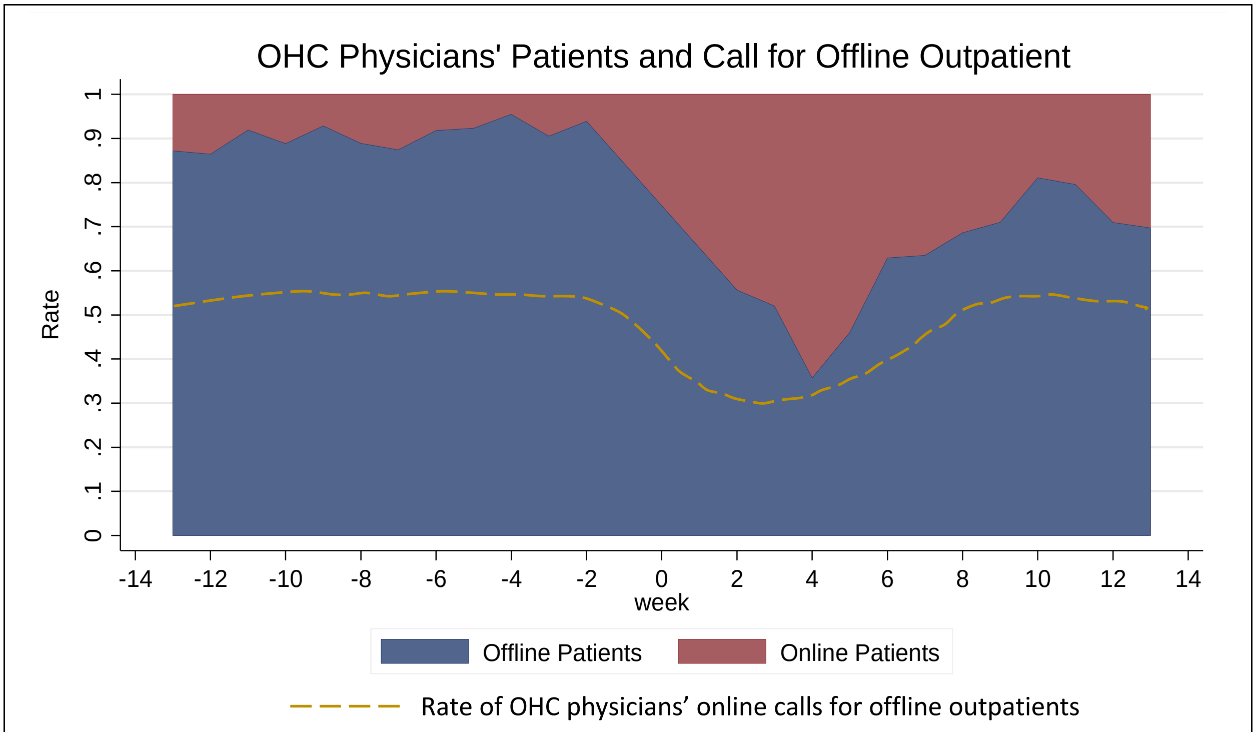

Figure 5. OHC Physicians' Patients

Next we employed the following DID specifications to examine the effects of COVID-19 outbreak on physicians' new patient acquisition:

$$\begin{aligned} new\_patient_{it} &= \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i \\ &+ \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} offline\_new\_patient_{it} &= \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i \\ &+ \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where $new\_patient_{it}$ is the logarithm of $New\_patient_{it}$ and $offline\_new\_patient_{it}$ is the logarithm of $Offline\_new\_patient_{it}$. Table 9 presents the results of the DID analysis and the results yield consistent patterns with our theoretical justifications. Specifically, for the resistance effect, OHC physicians acquired significantly more new patients than that of non-OHC physicians (i.e., positive $\widehat{\beta_1}$ in Column 1) and these new patients were mainly online new patients (i.e., insignificant $\widehat{\beta_1}$ for offline new patients in Column 3). In other words, because of these online new patients, the magnitude of the reduction in OHC physicians' production was lower than that of non-OHC physicians' production in the immediate period. On the other hand, for the recovery effect, OHC physicians also acquired more new patients (i.e., positive $\widehat{\beta_1}$ in Column 2) which were mainly offline ones (i.e., positive $\widehat{\beta_1}$ in Column 4).

Table 9. Digital Resilience on Physicians' New Patients

DV	***new_patient$_{it}$***		***offline_new_patient$_{it}$***	
Time Window	**[-6, -2] & [2, 6] (Resistance)**	**[-13,-7] & [7,13] (Recovery)**	**[-6, -2] & [2, 6] (Resistance)**	**[-13,-7] & [7,13] (Recovery)**
Column	(1)	(2)	(3)	(4)
OHC_physician$_i$ * outbreak$_t$	**0.42*** (0.13)**	**0.29** (0.12)**	**0.20 (0.13)**	**0.31*** (0.12)**
OHC_physician$_i$	0.46*** (0.07)	0.89*** (0.06)	0.54*** (0.07)	0.88*** (0.06)
outbreak$_t$	-0.63*** (0.11)	0.12 (0.11)	-0.56*** (0.10)	0.13 (0.11)
Control Variables	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of Physicians	154	154	154	154
Adj. R-Squared	0.73	0.73	0.75	0.76

Note: Standard errors in parentheses are robust and clustered by time and physician.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We also examined the moderating roles of sentiment and reputation on physicians' new patient acquisition. We adopted the same approach of constructing the subgroups of OHC physicians—i.e., groups of high vs. low positivity and high vs. low reputation. We then re-ran the analysis in Equations (4) and (5). The results are presented on Tables 10 and 11. In general, the results confirm that OHC physicians with high positivity of online consultations and high online reputation enjoyed stronger resistance and recovery effects.

Table 10. The OHC Physician's Sentiment and New Patients								
DV	***new_patient$_{it}$***				***offline_new_patient$_{it}$***			
Time Window	**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**		**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**	
Sentiment	positive	negative	positive	negative	positive	negative	positive	negative
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OHC_physician$_i$ * outbreak$_t$	**0.57*** (0.19)**	**0.28 (0.18)**	**0.33** (0.16)**	**0.25 (0.18)**	**0.36* (0.19)**	**0.05 (0.19)**	**0.42*** (0.15)**	**0.22 (0.18)**
OHC_physician$_i$	-2.24*** (0.10)	2.01*** (0.09)	-1.85*** (0.08)	2.80*** (0.09)	-2.16*** (0.09)	2.12*** (0.09)	-1.89*** (0.07)	2.80*** (0.09)
outbreak$_t$	-0.78*** (0.14)	-0.48*** (0.16)	0.02 (0.15)	0.20 (0.16)	-0.70*** (0.13)	-0.43*** (0.16)	0.03 (0.14)	0.23 (0.16)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Physicians	76	78	76	78	76	78	76	78
Adj. R-Squared	0.77	0.68	0.76	0.69	0.79	0.70	0.81	0.71
Note: Standard errors in parentheses are robust and clustered by time and physician. *** p < 0.01, ** p < 0.05, * p < 0.1								

Table 11. The OHC Physician's Reputation and New Patients								
DV	***new_patient$_{it}$***				***offline_new_patient$_{it}$***			
Time Window	**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**		**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**	
Reputation	high	low	high	low	high	low	high	low
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OHC_physician$_i$ * outbreak$_t$	0.46*** (0.17)	0.37* (0.21)	0.48*** (0.17)	0.05 (0.17)	0.44** (0.17)	-0.10 (0.21)	0.52*** (0.16)	0.06 (0.17)
OHC_physician$_i$	0.44*** (0.08)	-3.22*** (0.10)	0.79*** (0.08)	-3.62*** (0.08)	0.43*** (0.08)	-3.09*** (0.10)	0.77*** (0.08)	-3.63*** (0.09)
outbreak$_t$	-0.72*** (0.16)	-0.51*** (0.14)	-0.01 (0.16)	0.27* (0.16)	-0.73*** (0.16)	-0.35*** (0.12)	0.03 (0.15)	0.25* (0.15)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Physicians	86	68	86	68	86	68	86	68
Adj. R-Squared	0.74	0.71	0.69	0.77	0.74	0.76	0.73	0.80
Note: Standard errors in parentheses are robust and clustered by time and physician. *** p < 0.01, ** p < 0.05, * p < 0.1								

CHAPTER 5. GENERAL DISCUSSION

This study focuses on digital resilience in the healthcare setting in the context of the COVID-19 pandemic. Our contextualization provides an in-depth understanding of how physicians adopt and use OHCs to enhance their resilient responsiveness against exogenous shocks. In particular, we examine two forms of physicians' digital resilience—resistance and recovery effects— following a major pandemic outbreak. We find a resistance effect in the immediate period following the outbreak. Specifically, while the sudden outbreak of COVID-19 rendered offline healthcare ineffective, physicians who adopt an OHC to conduct online consultations enjoyed significantly lower levels of production losses than those who do not. Two major constituents of the resistance effect are *totally new online patients* and *those who switch* from the offline to the online channel. We also reveal a recovery effect in the subsequent period—OHC physicians' caseload volumes returned to normal levels more quickly than those of non-OHC physicians. New patients still constitute the majority of the online component of recovery and we provide evidence that one source of the offline recovery emerges from physicians' online consultations with patients who are called for offline visits. Finally, our subgroup analysis of OHC physicians not only demonstrates the roles of their overall online reputations and their specific online conversations with patients for enhancing digital resilience, but also provides further support for the use of the OHC artifact as a key mechanism underlying resistance and recovery.

5.1 Theoretical Contributions

Our study offers several contributions to IS research on digital resilience. First, we provide empirical support for the digital resilience of physicians who *adopt* OHCs in an understudied context—the major exogenous shock of the COVID-19 outbreak. Existing studies are primarily conducted in contexts where digital technologies are applied in building resilience to predictable disruptions, such as supply chain disruptions (Bakshi and Kleindorfer 2009) and data theft (Kwon and Johnson 2014). Digital technologies increase resilience by reducing the probability of the reoccurrence of disruptions. Our research context differs from the existing literature in that the healthcare system was disrupted by an unpredictable and unprecedented outbreak of the COVID-19 pandemic. Whether or not IT artifacts (OHCs in our case) can build digital resilience *after* such an exogenous shock has not been addressed by the literature. Moreover, prior research has mainly examined the overall resilient effect of digital technologies with data aggregated across different time periods of a disruption, thus offering a limited understanding of different digital resilience effects (e.g., Park et al. 2015). We identify two forms of digital resilience after a disruption—the resistance effect in the immediate period and the recovery effect in the subsequent period. Finally, matching online and offline data sources, our nature-experiment design, and controlling the demand-side/patient disease effects according to ICD codes enable us to identify and estimate the magnitude of these two effects. We also take a step forward by analyzing the sources of digital resilience effects through distinguishing between new and existing patients from both online and offline channels. While there is emerging research on the trend of resistance and recovery in the healthcare sector, the analysis was mainly conceptual and based on descriptions of the overall demand and supply of telemedicine services (e.g., Wosik et al. 2020). To the best of our knowledge, we are among the first to provide empirical evidence demonstrating both the existence and the sources of resistance and recovery effects in the healthcare sector.

Second, our subgroup analysis reveals that OHC physicians' *use* of the OHC platform, as reflected by the sentiment of their online consultations, enhanced resistance and recovery effects. This analysis further supports that it is the focal IT artifact—the OHC platform—that enables digital resilience in our case. We examine the role of a specific and direct metric of physicians' online behavior—the sentiment of physicians' conversations with their patients during online consultations. We conjecture that greater positivity of OHC physicians' conversations with their patients indicates a better physician-patient relationship. Potential patients are more likely to choose OHC physicians with a greater positivity expressed in online consultations, which in turn enhances physicians' digital resilience. We find significant resistance and recovery effects only for the high-positivity group, providing evidence that physicians' effective use of OHCs—as reflected by the sentiment of their online consultations—enhances resilience effects.

The role of reputation in online marketplaces has been studied in a number of contexts—for example, acquiring customized production contracts in the online labor marketplace (Lin et al. 2018) and strategic behavior to improve reputation in online exchange markets (Ye et al. 2014). In the healthcare setting, online ratings of physicians have been found to be positively associated with patient opinions about physician quality (Gao et al. 2012; Gray et al. 2015). In our research context, the overall ratings of physicians on the OHC platform represent the aggregation of patients' feedback on physicians' online service quality. We regard the rating as the overall online reputation of an OHC physician, which in turn influences patients' decision-making when choosing a physician for consultation. Thus, if the OHC enables digital resilience, OHC physicians with high reputations will benefit more than those with low reputations. The empirical findings support our conjecture—the high-reputation group enjoys significant resistance and recovery effects while these two effects were insignificant with the low-reputation group. The results thus again confirm that OHCs enable physicians' digital resilience.

Third, our research extends beyond the boundaries of healthcare research and bears implications for the business continuity and disaster recovery literature. From the information systems (IS) perspective, existing research on business continuity and disaster recovery has mainly focused on the management of technology risks, IS continuity (Niemimaa 2015), and security issues such as hackers, malicious users, and system malfunctions (Kananut et al. 2020). While a number of studies examining IT as supporting business continuity and recovery are emerging in such contexts as business operations (Margherita and Heikkilä forthcoming), critical infrastructure (Galbusera et al. 2021), and specific healthcare fields (Liow et al. 2020), most inquiries are *qualitative* ones. Our research provides the *quantitative* evidence that, in addition to supporting production in the context of normal operations, IT artifacts—OHCs in our case—may also serve as a technology enabler of business continuity and disaster recovery. IT users—OHC physicians in our case—can utilize IT to improve their level of resilient responsiveness against major unexpected shocks such as the COVID-19 pandemic. Our subgroup analysis also suggests that government and business organizations should carefully consider the characteristics of different IT users to motivate them to adopt and use IT in building organizational resilience (e.g., Kouvelis and Li 2008; Tomlin 2006). For instance, government policies and managerial interventions could be planned and implemented to encourage employees' IT adoption and utilization in order to facilitate the transition from maintaining business continuity to full disaster recovery (Fakhruddin et al. 2020). Our research thus provides a solid stepping stone to aid both theorizing and empirical analysis in this line of research.

5.2 Practical Implications

This research has several practical implications. First, considering that COVID-19 may exist in the long run and cause more waves of outbreaks in the future, our study highlights the key role of digital technologies in enhancing the digital resilience of healthcare entities against new outbreaks. In particular, IT enables both the immediate resistance and the subsequent recovery, meaning that different forms of digital resilience can be enhanced by different approaches. For example, to strengthen the resistance effect, OHC platforms may need to expand their capacity to manage online consultations right after an outbreak to accommodate the sudden increase in online consultation demand. Furthermore, to enhance the recovery effect, OHC platforms can help patients identify and make outpatient appointments and can provide additional information—both profile data and metrics about OHC physicians' overall performance and specific behaviors—to assist new patients in efficiently choosing the right physicians for online and offline consultations.

Second, and related to the above point, hospitals might consider encouraging physicians' adoption and use of OHCs. As demonstrated by our subgroup analysis, increased participation in OHCs by physicians and patients can contribute to generating the big data needed to facilitate patients' decision-making. OHC platforms can also assist physicians by facilitating their adoption and use of different online functionalities beyond telemedicine—e.g., encouraging physicians to post more articles and share their views with existing and potential patients. Physicians' utilization of OHC features can influence patients' decision-making and improve physician-patient relationships, thereby enhancing physicians' digital resilience.

Third, our research suggests that physicians' online ratings—i.e., their reputation—function as an important signal that helps new patients choose physicians in the context of disruptions. OHC platforms should consider optimizing the algorithm that calculates this overall rating to better reflect OHC physicians' service quality. For example, Gao et al. (2015) found that the online ratings of physicians may suffer from a bias "toward the upper end" because unsatisfied patients tend *not* to provide online ratings. Thus, a correction mechanism could be considered utilizing the offline data about physicians' service quality. This implies a collaboration between OHC platforms and hospitals to facilitate stronger digital resilience. In addition, unstructured online data could also be incorporated into the overall rating calculation, as implied by our findings of the sentiment of online conversations between physicians and patients.

5.3 Limitations and Future Research

This study has several limitations. First, we address the generalizability of our research findings. Because our research focuses on the first wave of the COVID-19 pandemic, there is a need to validate the application of our findings to subsequent outbreaks. While major outbreak waves are no longer unexpected, outbreaks are still hard to predict. Thus, we expect that the overall pattern of our results—e.g., the resistance and recovery aspects of digital resilience—will still apply. Moreover, another form of resilience— prevention—is not addressed in this study but is worthy of future research. Future research could explore whether the data gathered by OHCs concerning previous outbreaks could help predict the timing and significance of the next outbreak and thus exert a "prevention effect" to help both physicians and patients better prepare for the future. Furthermore, we encourage future studies to validate our findings regarding digital resistance and recovery effects with external shocks other than the COVID-19 pandemic and in other contexts beyond the healthcare setting. Finally, while the focal hospital offers the full spectrum of medical services and thus the physicians in our sample can largely represent physicians from different medical specialties, our results are based on data from a single hospital. We acknowledge the limitation regarding the generalizability of our findings and call for future research utilizing more representative samples.

Second, while we demonstrate that there are significant differences in digital resilience between OHC and non-OHC physicians and between subgroups of OHC physicians, we were not able to provide a comprehensive answer to why physicians self-select into different groups. Future research might consider a mixed method investigation of this key issue. One of our conjectures is that both IT skills and sociopsychological factors—e.g., computer self-efficacy and social comparison—may influence physicians' decision-making about the adoption and use of OHCs. Future research could employ both quantitative and qualitative methods to seek answers to these important questions.

Third, while we have incorporated ICD codes in our analysis to mitigate the issue of systematic differences between OHC and non-OHC channels, we cannot completely rule out the possible differences in the characteristics of demand between OHC and non-OHC channels. Also, other factors such as the differences in media richness between online and offline consultations (text-based mainly vs. face-to-face) may have potential influences on our research findings. We thus acknowledge these limitations and call for future research to control for or examine the potential impacts of these factors related to differences between OHC and non-OHC channels on physician production and performance.

CHAPTER 6. CONCLUSION

This study examines the resistance and recovery effects of physicians enabled by OHCs in the context of the major exogenous shock of the COVID-19 pandemic. We also demonstrate the heterogeneity effects of physicians' online reputation and the sentiment of online consultations on their digital resilience. This study contributes to research and practice by opening the black box of the various forms and sources of digital resilience across different time periods following a disruption. Our work offers a foundation for future research investigating the resilient effects of digital technologies when entities encounter unpredictable exogenous shocks.

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APPENDIX A

Logit Model for Propensity Score Matching: We ran a logit model to evaluate the possibility that a physician adopts to use OHC, in which the following physician-level variables were controlled: the physician's rank, age, gender, work experience, educational qualification, and the physician's ICD codes. We then matched the OHC physicians and non-OHC physicians using 1-1 nearest neighbor matching method (Guo and Fraser 2014). Table A1 reports the logit model results.

Table A1. Logistic Regression Result for PSM

DV	$OHC\_physician_i$
$title_i$	0.34 (0.24)
$gender_i$	-0.27 (0.25)
age_i	-0.04 (0.05)
$experience_i$	0.01 (0.04)
$education_i$	Yes
icd_codes_i	Yes
constant	-1.30 (1.59)
Pseudo R^2	0.02
No. of Observations	454
Note: *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$	

Descriptive Statistics of the Variables

Table A2. Descriptive Statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*25% Percentiles*	*Median*	*75% Percentiles*	*Max*
$Total\_consultation_{it}$	29.77	39.17	0.00	4.00	15.00	39.00	282.00
$Online\_consultation_{it}$	2.41	11.08	0.00	0.00	0.00	1.00	248.00
$Offline\_consultation_{it}$	28.57	37.69	0.00	3.00	14.00	38.00	253.00
$title_i$	1.97	0.84	1.00	1.00	2.00	3.00	3.00
$education_i$	1.00	0.00	1.00	1.00	1.00	1.00	1.00
$experience_i$	18.80	9.84	3.00	10.00	17.00	27.00	48.00
age_i	44.07	7.77	31.00	38.00	42.00	50.00	69.00
$gender_i$	1.46	0.50	1.00	1.00	1.00	2.00	2.00
new_case_t	27.22	37.09	0.00	0.00	6.00	33.00	93.00
$cured\_case_t$	213.60	127.20	0.00	123.00	307.00	310.00	314.00
$death\_case_t$	4.75	2.09	1.00	4.00	6.00	6.00	7.00
$sentiment_i$	0.38	0.18	0.00	0.33	0.41	0.50	0.77
$reputation_i$	3.05	0.24	2.40	2.90	3.00	3.10	4.00

Table A2. Descriptive Statistics							
Variable	***Mean***	***Std. Dev.***	***Min***	***25% Percentiles***	***Median***	***75% Percentiles***	***Max***
$New\_patient_{it}$	13.03	17.94	0.00	2.00	6.00	17.00	263.00
$Online\_new\_patient_{it}$	11.86	15.55	0.00	1.00	6.00	16.00	121.00
$Offline\_new\_patient_{it}$	2.34	11.03	0.00	0.00	0.00	1.00	248.00
$online\_new\_from\_offline_{it}$	0.89	3.54	0.00	0.00	0.00	0.00	38.00
$online\_totally\_new_{it}$	1.45	9.93	0.00	0.00	0.00	0.00	242.00

APPENDIX B

Validation Tests for the DID Analysis

<u>Testing Parallel Trend Assumption</u>: In the baseline and additional analysis, we mainly implemented the difference-in-differences analysis to explore the treatment effects; therefore, one potential concern is the parallel trend assumption. To further alleviate this concern, we utilized different unit root tests to examine whether the DVs in the treatment and control groups follow the same trend before the treatment. In line with the previous literature (e.g., Khern-am-nuai et al. 2018; Pamuru et al. 2021), we employed the Augmented Dickey-Fuller (ADF) test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Note that the null hypothesis of the ADF test is that a unit root is present in a time series or the time series is non-stationary, while the null hypothesis of the KPSS test is the time series is stationary. Hence we do expect the ADF test rejects the null hypothesis and the KPSS test accepts the null hypothesis, if the DVs in the treatment and control groups follow the similar trend before the treatment.

Table B1. Results of the Augmented Dickey Fuller test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test of stationary

	ADF test	KPSS test
$total\_consultation_{it}$	-14.492***	0.136
$offline\_consultation_{it}$	-10.647***	0.276

Table B1 reports the results from two different unit root tests – ADF test statistics rejects the null hypothesis for both total consultations and offline consultations as the DVs, respectively – in other words, the tests show that the DVs between the two groups are stationary. We find similar results using the KPSS tests. The KPSS test statistics cannot reject the null hypothesis (i.e., the time series is stationary), which translates to the acceptance of the parallel trend assumptions.

<u>Falsification Test 1 (Placebo Test)</u>: we created a “placebo event” at Week -6 and then applied the dataset from Week -13 to Week -1 to rerun the DID models. We expect the placebo event not having significant effects, as the pseudo-causal effects are known to be zero. The results show that the placebo event (Week -6) has no significant effect on the DVs.

Table B2. Falsification Test: Placebo Analysis

Time Window	Week [-13,-1]					
Placebo event week	Week -6					
DV	*$total\_consultation_{it}$*			*$offline\_consultation_{it}$*		
Column	(1)	(2)	(3)	(4)	(5)	(6)
$OHC\_physician_i$ * $Pseudo\_outbreak_t$	**0.04 (0.08)**	**0.04 (0.08)**	**0.04 (0.08)**	**0.11 (0.07)**	**0.11 (0.08)**	**0.11 (0.08)**
$Pseudo\_outbreak_t$	-0.33 (0.22)	-0.60*** (0.05)	-0.61*** (0.02)	-0.45** (0.23)	-0.86*** (0.07)	-0.80*** (0.02)
$OHC\_physician_i$	0.01 (0.04)	0.01 (0.04)	0.10 (0.07)	0.01 (0.04)	0.01 (0.04)	0.11* (0.07)
Control Variables	No	Yes	Yes	No	Yes	Yes
Physician FE	No	No	Yes	No	No	Yes
Time FE	No	No	Yes	No	No	Yes
No. of Physicians	154	154	154	154	154	154
Adj. R-Squared	0.01	0.86	0.86	0.02	0.89	0.89

Note: Standard errors in parentheses are robust and clustered by time and physician.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

<u>Falsification Test 2 (Chinese New Year effect)</u>: we conducted an additional placebo test for ruling out the concern that the findings are possibly driven by the Chinese New Year effects. We utilized the Chinese New Year week in 2019 as the second "placebo event," and further collected the 28 weeks' data around the 2019 Chinese New Year week to examine the treatment effect of the placebo event. Table B3 shows that the pseudo-causal effect is insignificant and we conclude that our findings are not driven by the Chinese New Year effect. Thus, our baseline analysis generates credible causal evidence.

Table B3. Falsification Test: Chinese New Year Effect												
DV	***total_consultation**$_{it}$*						***offline_consultation**$_{it}$*					
Time Window	**[-6,-2] & [2,6]**			**[-13,-7] & [7,13]**			**[-6,-2] & [2,6]**			**[-13,-7] & [7,13]**		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
***OHC_physician**$_i$ * **festival**$_t$*	**0.01 (0.09)**	**0.01 (0.10)**	**0.01 (0.10)**	**-0.18 (0.11)**	**-0.18 (0.12)**	**-0.18 (0.12)**	**0.00 (0.09)**	**0.00 (0.10)**	**0.00 (0.10)**	**-0.14 (0.12)**	**-0.14 (0.12)**	**-0.14 (0.12)**
OHC_physician$_i$	0.07 (0.23)	-0.79*** (0.11)	-0.71*** (0.05)	0.07 (0.23)	-0.25** (0.10)	-0.17*** (0.06)	-0.07 (0.24)	-0.92*** (0.09)	-0.84*** (0.05)	-0.06 (0.23)	-0.39*** (0.10)	-0.31*** (0.06)
festival$_t$	0.08 (0.07)	0.28*** (0.10)	0.43** (0.20)	0.11 (0.08)	-1.14** (0.56)	-0.45 (1.13)	0.08 (0.07)	0.24** (0.09)	0.41** (0.20)	0.11 (0.08)	-0.96* (0.55)	-0.28 (1.07)
Control Variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Physician FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
No. of Physicians	154	154	154	154	154	154	154	154	154	154	154	154
Adj. R-Squared	0.00	0.86	0.87	0.00	0.83	0.83	0.00	0.86	0.87	0.00	0.82	0.82

Note: Standard errors in parentheses are robust and clustered by time and physician.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

<u>Different Thresholds of Recovery</u>: we alternatively used Week 6 and Week 8 as thresholds for the subsequent period to run the DID models to examine that whether our findings are sensitive to the thresholds for the intermediate and subsequent periods. The results are presented in Table B4 and we observe similar patterns to our main findings. Thus we conclude that our empirical findings are robust and insensitive to the choice of thresholds for resistance and recovery periods.

Table B4. Different Thresholds of Recovery and Digital Resilience								
Threshold of Recovery	***Week 6***				***Week 8***			
DV	***total_consultation**$_{it}$*		***offline_consultation**$_{it}$*		***total_consultation**$_{it}$*		***offline_consultation**$_{it}$*	
Time Window	**[-5, -2] & [2, 5] (Resistance)**		**[-13,-6] & [6,13] (Recovery)**		**[-7, -2] & [2, 7] (Resistance)**		**[-13,-8] & [8,13] (Recovery)**	
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
***OHC_physician**$_i$ * **outbreak**$_t$*	**0.37** (0.16)**	**0.28** (0.13)**	**0.15 (0.16)**	**0.29** (0.13)**	**0.37*** (0.14)**	**0.25* (0.14)**	**0.21 (0.15)**	**0.28* (0.14)**
OHC_physician$_i$	0.27*** (0.08)	-0.89*** (0.07)	-0.55*** (0.08)	-1.12*** (0.07)	0.02 (0.07)	-1.02*** (0.07)	-0.70*** (0.07)	-1.16*** (0.07)
outbreak$_t$	25.03*** (8.36)	-3.57*** (1.33)	30.21*** (6.95)	-2.85** (1.26)	5.69 (3.84)	-3.55*** (1.34)	6.67* (3.61)	-2.84** (1.28)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Physicians	154	154	154	154	154	154	154	154
Adj. R-Squared	0.78	0.75	0.79	0.78	0.77	0.76	0.78	0.79

Note: Standard errors in parentheses are robust and clustered by time and physician.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$