Operational and Behavioral Interventions to Jointly Manage Telemedicine and In-person Channels in Epidemic Contexts

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This is to certify that I have examined this copy of a doctoral dissertation by

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ABSTRACT

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This thesis investigates a multichannel healthcare system and studies operational and behavioral interventions to manage provider decisions and patient demand for telemedicine and in-person channels in the presence of an infection risk. The first part of the thesis formulates an optimization model that determines optimal capacity allocation and pricing decisions for the channels to maximize the provider's revenue. The main novelty in our model is that the in-person channel has a contagion disutility driven by patients' fear of contracting the disease in the healthcare center. The contagion disutility has two components: a behavioral parameter capturing the contagion awareness of patients and a contagion function. The contagion disutility is increasing in the number of in-person appointments, which makes the patient's choice endogenous.

The optimization model offers several interesting results. We prove that if there is a contagion disutility and the telemedicine channel is not offered, the revenue grows logarithmically in potential demand (patient pool). However, the revenue grows linearly in potential demand if the telemedicine channel is offered. Therefore, the telemedicine channel is necessary to mitigate the provider's revenue loss due to contagion disutility. Additionally, when only the in-person channel is offered, patient access (total number of appointments) decreases significantly. We prove that the optimal telemedicine appointment price is strictly less than that of the in-person appointment, and the price gap increases as the patients become more contagion-aware. When we include the physician's sickness due to contracting the disease from patients in our model, we see that a social planner maximizing the welfare allocates more capacity to telemedicine than a revenue-maximizing provider, making

physicians better off. The first part of the thesis shows that capacity allocation and pricing decisions that incorporate patients' contagion disutility can mitigate revenue losses experienced by healthcare providers during epidemics. This result continues to hold when some telemedicine appointments may require follow-up in-person appointments if the likelihood of a follow-up appointment is under a certain value. We study a setting where we include the direct cost of sick patients (disease burden) in the provider's/social planner's objective. When the disease burden is sufficiently large, high contagion awareness among patients can increase revenue/welfare. This indicates the importance of modulating patients' contagion awareness levels.

Considering the benefits of telemedicine in a context of infection risk, in the second part of the thesis, we test the effectiveness of several operational and behavioral interventions in increasing the use of telemedicine during epidemics. We conduct a series of laboratory/platform experiments, in which each study considers an operational dimension alongside a behavioral one. The operational dimensions are motivated by the optimal capacity allocation and pricing decisions we studied in the first part of the thesis and include appointment prices and wait times. The behavioral dimensions include infection fear and health condition deterioration over time. The novelty of our experiments is that they include both dimensions in an epidemic context and let participants actively choose between the telemedicine and in-person appointment options. Our study is the first to propose and test informational interventions to manage patient demand between channels in an epidemic context via controlled experiments. Our experimental setting also allows us to control for behavioral characteristics such as risk perception and inherent attitudes toward the channels that can impact channel choice.

The first operational dimension that we study is a price difference intervention where the price of an in-person appointment is 25% higher than that of a telemedicine appointment. Although we observe a directional increase in the use of telemedicine, the impact is not significant. Insurance considerations, a need for increased saliency, or a larger price difference can be potential explanations. The second operational dimension is the appointment wait time advantage of the telemedicine channel. We approach appointment wait time from two different perspectives: the systems perspective and the patient's perspective. In the systems perspective, due to the provider's capacity/resource allocation policy, telemedicine appointments have shorter appointment wait times. In the patient's perspective, the provider offers similar appointment wait times for the channels. Yet, telemedicine appointments can easily fit into the schedule of patients due to their convenience in eliminating the need to travel to a healthcare facility. That can allow patients to see the doctor sooner.

In addition to the operational interventions, we test the effectiveness of several behavioral (informational) interventions. In line with the benefit of increasing patients' contagion awareness in the first part of the thesis, the first set of informational interventions aims to increase the infection risk awareness of patients and nudge them to choose the telemedicine channel. The infection messages differ in their framing (negative or positive) and risk focus (only self-risk or including the risk for others). For the messages regarding the appointment wait time difference, we emphasize that telemedicine appointments allow patients to see the doctor sooner. When there is an appointment wait time difference due to the provider's capacity/resource allocation policy, informational interventions do not further nudge patients toward the telemedicine channel. When the provider offers similar appointment wait times, the informational interventions can be effective in increasing the use of telemedicine. We observe that a negatively framed infection message (emphasizing the infection risk associated with the in-person channel for self and others) and a positively framed convenience message (emphasizing the ease of scheduling for the telemedicine channel) effectively increase telemedicine use. The convenience message has the advantage of being further used in non-epidemic contexts, increasing its generalizability. Overall, the results of the second part of the thesis show that healthcare providers can manage patient demand with easy-to-apply informational messages. Together, the findings of this thesis offer actionable insights for healthcare providers to manage channel decisions and patient demand in multichannel healthcare systems.

ÖZETÇE

Salgın Dönemlerinde Teletıp ve Yüz Yüze Hizmet Kanallarının Eşgüdümlü Yönetimine Yönelik Operasyonel ve Davranışsal Müdahaleler
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Bu tez, salgın dönemlerinde, çok kanallı sağlık hizmeti sağlayıcısının kararlarını ve hastaların yüz yüze ve uzaktan sağlık (teletıp) kanallarına olan talebini yönetmeye yönelik operasyonel ve davranışsal müdahaleleri incelemektedir. Tezin ilk bölümünde, sağlayıcının gelirini maksimize etmek amacıyla kanallar için optimal kapasite tahsisi ve fiyatlandırma kararlarını belirleyen bir optimizasyon modeli geliştirilmiştir. Modelin temel yeniliği, yüz yüze kanalın sağlık merkezinde hastalığa yakalanma korkusu kaynaklı olumsuz etki (bulaş olumsuzluğu) içermesidir. Bulaş olumsuzluğu iki bileşenden oluşmaktadır: hastaların bulaş farkındalığını yansıtan davranışsal bir parametre ve bulaş fonksiyonu. Bulaş olumsuzluğu, yüz yüze randevu sayısı arttıkça yükselmekte ve bu durum hastaların kanal tercihlerini içsel (endojen) hâle getirmektedir.

Optimizasyon modeli birkaç ilginç sonuç sunmaktadır. Eğer bulaş olumsuzluğu varsa ve teletıp sunulmuyorsa, sağlayıcının geliri potansiyel talep (hasta havuzu) karşısında logaritmik olarak artar. Buna karşılık, teletıp hizmeti sunuluyorsa, gelir potansiyel taleple doğrusal olarak artar. Dolayısıyla, bulaş olumsuzluğundan kaynaklanan gelir kaybını azaltmak için teletıp gereklidir. Ayrıca, yalnızca yüz yüze kanal sunulduğunda hasta erişimi (toplam randevu sayısı) önemli ölçüde azalmaktadır. Teletıp randevusunun optimal fiyatının yüz yüze randevudan daha düşük olduğu ve fiyat farkının, hastaların bulaş farkındalığı arttıkça büyüdüğü ispatlanmıştır. Modele doktorların hastalığı hastalardan kaparak hastalanması durumu dahil edildiğinde, sosyal faydayı maksimize eden bir sosyal planlayıcının, geliri maksimize eden bir sağlayıcıya kıyasla teletıp kanalına daha fazla kapasite ayırdığı ve bunun da doktorları koruduğu görülmektedir. Tezin ilk bölümü, hastaların bulaş

olumsuzluğunu dikkate alan kapasite tahsisi ve fiyatlandırma kararlarının, salgınlar sırasında sağlık hizmeti sağlayıcılarının yaşadığı gelir kayıplarını azaltabileceğini ortaya koymaktadır. Bu sonuç, bazı teletıp randevularının yüz yüze takip randevusu gerektirdiği durumlarda da geçerliliğini korumakta; ancak bu geçerlilik, takip randevusu olasılığı belirli bir eşik değerin altında kaldığında sürmektedir. Ayrıca, sağlayıcının ya da sosyal planlayıcının amaç fonksiyonuna hasta bireylerin hastalık maliyeti (hastalık yükü) doğrudan dahil edildiğinde ve bulaş riski farkındalığının yeterince yüksek olduğu durumlarda bu farkındalık sağlayıcının gelirini ya da sosyal faydayı artırabilir. Bu, hastaların bulaş riski farkındalığının seviyesini doğru biçimde yönlendirmenin önemine işaret etmektedir.

Bulaş riski bağlamında teletıbbın faydaları göz önünde bulundurularak, tezin ikinci bölümünde salgınlar sırasında teletıp kullanımını artırmaya yönelik çeşitli operasyonel ve davranışsal müdahalelerin etkinliğini test edilmiştir. Bu amaçla, her birinde bir operasyonel ve bir davranışsal boyutun birlikte ele alındığı bir dizi laboratuvar/platform deneyi yürütülmüştür. Operasyonel boyutlar, tezin ilk bölümünde incelenen optimal kapasite tahsisi ve fiyatlandırma kararlarından ilham almakta olup randevu fiyatları ve bekleme sürelerini kapsamaktadır. Davranışsal boyutlar ise bulaş korkusu ve zamanla kötüleşen sağlık durumu gibi unsurları içermektedir. Deneylerin yeniliği, bu iki boyutu bir arada ele alarak bir salgın bağlamında katılımcıların yüz yüze ve uzaktan randevu seçenekleri arasında aktif seçim yapmalarına olanak tanımasıdır. Çalışmamız, salgın bağlamında hasta talebini kanal bazında yönetmek amacıyla bilgi temelli müdahaleleri öneren ve kontrollü deneylerle test eden ilk çalışmadır. Deneysel kurgu, aynı zamanda kanal tercihlerini etkileyebilecek risk algısı ve kanallara yönelik bireysel tutumlar gibi davranışsal özellikleri kontrol etmeye olanak sağlamaktadır.

İncelediğimiz ilk operasyonel boyut, yüz yüze randevu fiyatının teletıp randevu fiyatından %25 daha yüksek olduğu bir fiyat farkı müdahalesidir. Teletıp kullanımında yönsel bir artış gözlense de, bu etkinin istatistiksel olarak anlamlı olmadığı görülmektedir. Bu sonucu açıklayabilecek olası nedenler arasında sigorta kapsamı ile ilgili beklentiler, müdahalenin yeterince dikkat çekici olmaması (düşük belirginlik) ya da daha büyük bir fiyat farkına ihtiyaç duyulması yer almaktadır. İkinci operasyonel boyut ise, teletıp kanalının randevu bekleme süresi açısından sağladığı avantajtır. Randevu bekleme süresi konusuna hem sistem düzeyinden hem de hasta perspektifinden yaklaşılmaktadır. Sistem düzeyinde, sağlayıcının kapasite/kaynak tahsis politikası nedeniyle teletıp randevuları daha kısa bekleme süresi ile sunulmaktadır. Hasta perspektifinde ise, her iki kanal için benzer randevu bekleme süreleri söz konusu olduğunda dahi, teletıp randevuların sağlık kuruluşuna fiziksel olarak gitmeyi gerektirmemesi, hastaların kendi programlarına daha kolay entegre edilebilmesini sağlayabilir. Bu da hastaların doktora daha erken ulaşabilmesine olanak tanıyabilir.

Operasyonel müdahalelere ek olarak, çeşitli davranışsal (bilgilendirici) müdahalelerin etkinliği test edilmiştir. Tezin ilk bölümünde hastaların bulaş riski farkındalığının artırılmasının sağladığı faydayla tutarlı olarak, ilk grup bilgilendirici müdahaleler, bu farkındalığı artırmayı ve hastaları teletıp kanalına yönlendirmeyi amaçlamaktadır. Bu bulaş temalı mesajlar, çerçeveleme biçimine (olumsuz ya da olumlu) ve risk odağına (sadece kişinin kendisi için risk ya da hem kendisi hem başkaları için risk) göre farklılık göstermektedir. Randevu bekleme süresi farkına yönelik mesajlarda ise, teletıp randevuların hastaların doktora daha erken ulaşmasını sağladığı vurgulanmaktadır. Sağlık hizmeti sağlayıcısının kapasite/kaynak tahsis politikası nedeniyle oluşan bekleme süresi farkı durumunda, bilgilendirici müdahaleler hastaları teletıp kanalına yönlendirme konusunda ek bir katkı sağlamamaktadır. Ancak sağlayıcının her iki kanal için benzer bekleme süreleri sunduğu durumda, bilgilendirici müdahaleler teletıp kullanımını artırmada etkili olabilmektedir. Deneylerimizde, olumsuz çerçevelenmiş bulaş mesajı (yüz yüze kanalın hem bireyin kendisi hem de diğerleri için oluşturduğu bulaş riski vurgusu) ve olumlu çerçevelenmiş kolaylık mesajı (teletıp kanalının programlamadaki esnekliği vurgusu) teletıp kullanımını anlamlı biçimde artırmaktadır. Kolaylık mesajı ayrıca, salgın olmayan bağlamlarda da kullanılabilme potansiyeline sahip olması sayesinde daha geniş bir uygulama alanına sahiptir. Genel olarak, tezin ikinci bölümünün bulguları, sağlık hizmeti sağlayıcılarının uygulaması kolay bilgi temelli mesajlarla hasta talebini yönetebileceğini göstermektedir. Bu tez çalışmasının bulguları, çok kanallı sağlık hizmeti sağlayıcılarına hem kanal yönetimi hem de hasta talebi yönetiminde kullanılabilecek somut ve uygulanabilir yöntemler sunmaktadır.

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Chapter 1

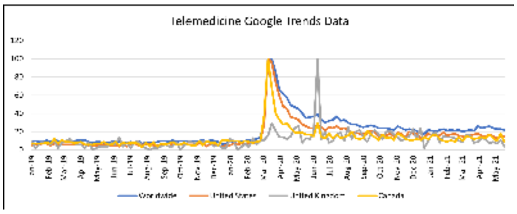
INTRODUCTION

Telemedicine, which is defined as the delivery of medical care and provision of general health services from a distance (Hyder and Razzak 2020), offers several benefits. It eliminates transportation barriers (Haleem et al. 2021), which leads to increased access to care (Barbosa et al. 2021, Palozzi et al. 2020). It improves clinical outcomes and patient satisfaction (Barbosa et al. 2021, Ezeamii et al. 2024), and reduces patients' average length of stay in the emergency department (Sun et al. 2020). Telemedicine decreases costs, especially in conditions with high virtualization potential (Ayabakan et al. 2024). Patients are more likely to attend their scheduled telemedicine appointments compared to in-person visits (Cummins et al. 2024, Haggerty et al. 2022), which increases the efficiency of resources for healthcare providers (Drerup et al. 2021). From an environmental perspective, telemedicine decreases greenhouse gas emissions, helping to create a more sustainable healthcare system (Thiel et al. 2023). These advantages of telemedicine underline its importance in a multichannel healthcare delivery system.

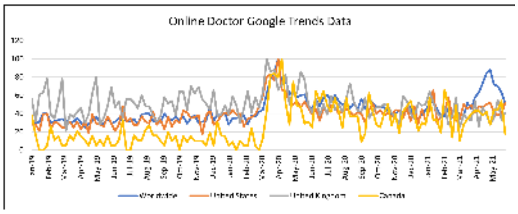
During an epidemic, telemedicine takes on an additional role. It helps to mitigate the spread of infection (Gao et al. 2020, Gohari et al. 2021) and protect patients and healthcare workers during viral disease epidemics (Haleem et al. 2021). Due to increased wildlife interventions, climate change, and urbanization, epidemic risks are escalating (Gostin 2022). The probability of occurrence of extreme epidemics is expected to increase up to threefold in the future (Marani et al. 2021). There is empirical evidence that patients who are seen in a healthcare facility after a patient with an influenza-like illness are more likely to return with flu-like symptoms compared to non-exposed patients (Neprash et al. 2021). In this new era, the role of the telemedicine channel in terms of reducing the risk of contracting communicable diseases is significant.

The COVID-19 pandemic had an impact on the patient demand for seeking care. While the demand for in-person care has decreased, the demand for telemedicine has significantly increased. NHS Digital data shows that in England, the daily percentage of face-to-face appointments with general practitioners has declined sharply after COVID-19 (Economist 2020a). Between January 2020 and February 2021, there is a median decline of 56% in in-person outpatient care utilization (Dupraz et al. 2022). In the United States, the number of telemedicine visits increased by 50% during January-March 2020, compared to the same period in 2019 (Koonin et al. 2020). In 2019, 11% of US consumers used telemedicine. This number increased to 46% in 2020, and 76% of the consumers stated that they are thinking of using it moving forward (Bestsennyy et al. 2020). Friedman et al. (2022) uses insurance claim data and reports an increase in the mean weekly telemedicine appointments from 773 to 45,632, comparing pre-pandemic and pandemic periods in the year 2020. McKinsey expects global digital health revenues to increase from \$350bn in 2019 to \$600bn in 2024 (Economist 2020b). Figure 1.1 presents Google Trends for telemedicine, online doctor, online shopping, and food delivery search topics. We observe a sharp increase in the searches of these online services with the start of the pandemic worldwide, in the United States, in the United Kingdom, and in Canada data. This change illustrates the impact of infection risk in shaping consumer behavior.

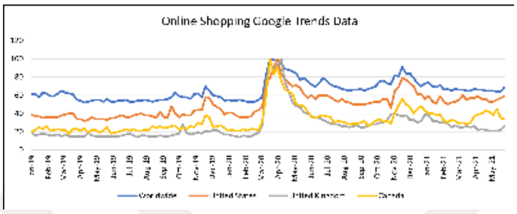
The fear of getting infected at healthcare facilities plays an important role in shaping patient demand. Some patients use telemedicine to seek care. Some patients delay needed care due to the fear of contracting the virus at the healthcare facilities (Lazzerini et al. 2020a, Wong et al. 2020, Arnetz et al. 2022). There is a positive correlation between reported COVID-19 prevalence rates and demand for telemedicine (Weiner et al. 2021), which supports the claim that fear is one of the determinants of patient choice. Patients are not the only ones who are at risk. WHO (2020) stated that 14% of all reported COVID-19 cases are healthcare work-



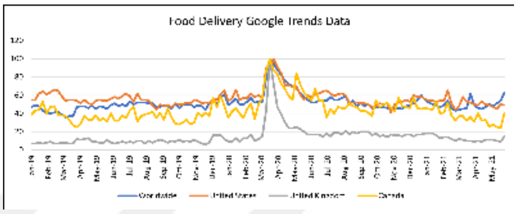
(a) telemedicine



(b) online doctor



(c) online shopping



(d) food delivery

Figure 1.1: Google trends data for online services (scaled on 0-100): (a) telemedicine, (b) online doctor, (c) online shopping, (d) food delivery

ers. Guardian and KHN (2021) announced 3,607 healthcare worker deaths in the US due to COVID-19 as of April 2021, the majority of them being nurses (32%), healthcare support (20%), and physicians (17%). As the duration of an epidemic increases and the number of cases goes up, healthcare workers' risk further increases. This puts hospitals under pressure and encourages telemedicine to be utilized to its full potential. Indeed, an increasing number of hospitals around the world provide telemedicine appointments in which physicians diagnose a patient's condition through a web-based application. Patients can share their test results in these virtual appointments free of charge within a given time period after the test is applied. Depending on the hospital policy, online prescriptions can be provided following a telemedicine appointment. Figure 1.2 shows the impacts of demand loss driven by the fear of infection and capacity loss driven by the sick healthcare workers on the healthcare providers. Healthcare providers should consider the changes in demand and capacity during an epidemic to mitigate access and revenue losses.

In Chapter 3, the impact of an epidemic on the healthcare providers is studied through its effect on patient demand. Specifically, patients are contagion-aware,

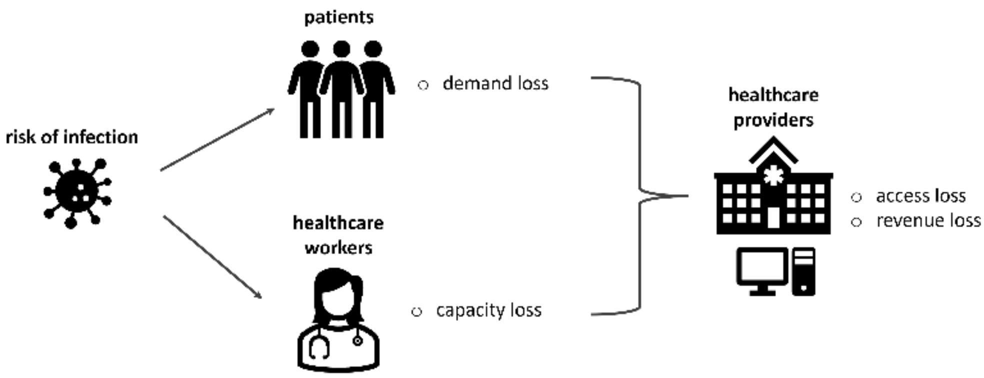


Figure 1.2: The impact of epidemics on healthcare providers

and they consider the contagion effect in their channel choice for telemedicine versus in-person channels. First, an optimization model is formulated that provides the optimal telemedicine and in-person capacities to offer at fixed prices. We prove that the healthcare provider incurs a significant revenue loss due to the effect of contagion, and this revenue loss is because of the logarithmic increase in the number of in-person appointments while the potential demand increases linearly. Next, the benefit of offering telemedicine during an epidemic is discussed by comparing the provider revenues with and without telemedicine. After the model with fixed prices, a pricing optimization model is formulated that optimizes prices in addition to the capacities. The optimal in-person price is higher than that of the telemedicine price under the contagion effect, where the price gap increases with an increase in the contagion awareness of the patients. Similar to the fixed price case, the healthcare provider's revenue loss is significant due to the effect of contagion under the optimal prices. After discussing the contagion effect through the choices of the patients, the model is extended to include the effect of contagion on the physicians. In more detail, effective capacity decreases with the in-person appointments due to physicians catching the disease at the clinic and not showing up for work. Under this setting, two different objectives are analyzed. One is revenue maximization, in which the contagion effect is considered through the appointment choices of the patients. Another is welfare maximization, where, in addition to the patients' contagion awareness, the provider also considers the welfare of society in the decision of the optimal prices and capacities through patient utilities. When the provider maximizes the revenue, it offers higher in-person capacity than the socially optimal level, making physicians worse off. Next, the setting where the provider can manage patients' contagion awareness is studied, and the benefit of having fully contagion-aware patients on both revenue and welfare is illustrated. Finally, the case where the telemedicine channel is partially effective, leading to in-person revisits with a certain probability, is studied.

Despite the increase in telemedicine use, visit rates remained at or below 50% even for mental health (Mulvaney-Day et al. 2022, Hunsinger et al. 2021), which is the medical specialty with the highest telehealth utilization rate (Drake et al. 2022, Hsiao et al. 2023). This shows that there is room for improvement to increase telemedicine adoption. One can manage patient demand between the channels with pricing and capacity allocation interventions (as we did in Chapter 3), or through modulation of patient infection fear with informational interventions (nudge messages). While pricing and capacity allocation policies are system-wide changes that can take significant time and effort to implement, informational interventions can be easily integrated into health systems depending on the evolution of an epidemic. In Chapter 4, in addition to direct controls such as a price difference, we consider the impact of informational interventions in patient demand management. Motivated by the findings of Chapter 3, we mimic patients' channel choices during epidemics within a laboratory setting. This allows us to control for the characteristics of the two channels that have a major impact on patients' decisions: price, appointment wait time, infection risk for the in-person channel, and revisit risk for the telemedicine channel. We consider appointment wait time (time until the next available appointment) in our setting as it is an observable outcome of the provider's capacity management policy, which is found to be effective in determining the appointment channel choice of the patients (Buchanan et al. 2021, Imlach et al. 2020, Mozes et al. 2022, von Weinrich et al. 2022).

The informational interventions that we study emphasize either infection risk or appointment wait time (dis)advantages of the channels. The infection messages that we use differ in their framing (positive or negative) and in whether they emphasize only self-risk or include the risk to others (prosocial component). For appointment wait time messages, a positive framing is preferred, highlighting the benefit of seeing a doctor sooner by making an online appointment. We approach the appointment wait time from two perspectives: the systems and the patients. In the systems perspective, the provider offers different appointment wait times for the two channels as a result of its capacity management policy. In the patients perspective, which is referred to as convenience, the provider offers similar availability for the channels. A potential appointment wait time difference arises due to patients' scheduling conflicts. Specifically, a telemedicine appointment can be fitted into a patient's schedule more easily compared to an in-person appointment due to the elimination of transportation-related time and effort, allowing more timely access. We conduct several behavioral laboratory experiments. All studies use a between-subjects design, controlling for participants' infection risk attitudes and existing channel preferences through established scales.

This thesis offers several contributions to the literature on multichannel healthcare delivery. The optimization model formulated in this thesis is the first to acknowledge contagion-aware patient channel choice and to show its impact on optimal channel decisions and the healthcare provider's revenue. The experimental part is the first to test the effectiveness of both operational and behavioral mechanisms on patients' channel choices during epidemics. It analyzes the difference between the appointment wait time of the channels from both healthcare providers' and patients' perspectives and provides a holistic approach.

The rest of the thesis is structured as follows. In Chapter 2, a brief literature review is provided consisting of an overview of the literature on telemedicine's effectiveness, efficiency, and impact on accessibility, the literature on multichannel healthcare delivery models, and the literature on informational interventions in healthcare. Chapter 3 provides the optimization model that offers optimal capacity allocation and pricing for the in-person and telemedicine channels with contagion-aware patient choice. Chapter 4 presents the laboratory experiments that test the effectiveness of several interventions to increase patient choice for the telemedicine channel during epidemics or respiratory virus seasons. Finally, Chapter 5 concludes the thesis and discusses future research directions.

Chapter 2

LITERATURE REVIEW

2.1 Telemedicine: Effectiveness, Efficiency, and Accessibility

Telemedicine is found to be effective, positively affecting clinical outcomes, especially for conditions requiring close monitoring and early intervention (DelliFraine and Dansky 2008). A randomized controlled trial for Parkinson's disease shows the improvement of quality of life and motor performance of the patients by telemedicine (Dorsey et al. 2010). According to a study of patients with heart failure, telemedicine increases patients' quality of life and decreases duration spent at the hospital (Domingo et al. 2011). The effectiveness of telemedicine can differ among medical specialties. We acknowledge the possibility for relatively low effectiveness by considering an in-person revisit that may be required after a telemedicine appointment (see Wang et al. (2023), Zychlinski (2023), Liu and Armony (2024), Çakıcı and Mills (2025), and Liu et al. (2025) for other papers considering revisits).

Regarding efficiency and accessibility, telemedicine eliminates transportation barriers (Kessler et al. 2016, Dullet et al. 2017, Wang et al. 2020), improves provider availability, and decreases waiting times (Barbosa et al. 2021). Offering telemedicine in emergency rooms decreases the average length of stay (LOS) of the patients, and this effect is partially driven by the flexible resource allocation (Sun et al. 2020). Offering e-visits increases physician revenue and panel size under proportional fee-for-service e-visit compensation (Bavafa et al. 2021). Implementing asynchronous telemedicine, where patients and physicians communicate at different times rather than in real-time, increases the total number of patients seen in both in-person and telemedicine channels, improving overall system efficiency (Tushe et al. 2025). Empirical evidence shows that opening a telemedicine center increases the overall network visit rate, and a substantial portion of this increase is due to new patients (Delana et al. 2023). In another empirical study, the introduction of video visits is shown to increase the demand for in-person primary care provider visits, where most of the demand is driven by patients with poorer access to in-person care (Lekwijit et al. 2023). Finally, Hwang et al. (2022) provide empirical evidence on the impact of teleconsultations in connecting physicians from resourceful areas with patients from underserved areas. We consider efficiency and accessibility from the perspective of infection risk avoidance via the telemedicine channel in Section 3.

In Section 4, in addition to the infection risk avoidance, we consider another dimension of efficiency and accessibility of telemedicine: the appointment wait time. Telehealth visits are associated with shorter appointment wait times (MAHSO 2021, Graetz et al. 2022, Tilley 2022, Pullyblank et al. 2024), where the appointment wait time difference depends on the specialty. For ulcer patients, the median waiting time is 25 days for a video consultation and 32 days for an in-person consultation (Wickström et al. 2018). For mental health, median wait times for telepsychiatry and in-person appointments are 43 days and 67 days (Sun et al. 2023). For outpatient follow-up stroke care, an e-visit has a shorter wait time, with a mean of 60 days, compared to an in-person visit, which has a mean wait time of 78 days (Appireddy et al. 2019). Around 60% of general practitioners offer in-person services with similar wait times to virtual services, while 22% offer face-to-face services with a significantly higher wait time compared to a remote service (Kaffash 2023). The time between patient referral and the date of the booked visit is 45±22 days for a teleglaucoma patient and 88±47 days for an in-person visit (Arora et al. 2014). These findings support the advantage of telemedicine in reducing patient wait times.

2.2 Multichannel Healthcare Delivery

Betcheva et al. (2021) emphasize the importance of telemedicine in redesigning healthcare supply chains. In line with this, our research explores the joint management of the in-person and telemedicine channels. Some studies on multichannel healthcare delivery take the perspective of a central decision-maker and do not consider patient decisions (Erdogan et al. 2018, Bayram et al. 2020, Yu and Bayram 2021, Adida and Bravo 2023). In our model in Section 3, patients choose between telemedicine, in-person, and an outside option according to a discrete choice model (specifically, the multinomial logit (MNL) model). There is a stream of work on healthcare models that consider patient choice (Gupta and Wang 2008, Feldman et al. 2014, Liu et al. 2019, Cayirli et al. 2019, Tunçalp and Örmeci 2024). Our choice model is different from the extant literature by modeling an endogenous infection risk, which creates a negative network effect (see Katz and Shapiro (1985) as an example of models with network externalities). More specifically, we consider an endogenous demand where the choice probabilities of the patients in the MNL model are determined by the proportion of those selecting the in-person channel in equilibrium. This is methodologically similar to what Du et al. (2016) and Wang and Wang (2017) do in the retail context. They study pricing decisions under an MNL model with endogenous network effects. Specifically, in their models, the utility of a product depends on its total consumption. Unlike those two papers, we first study capacity allocation decisions under fixed prices, where it may be optimal to offer different sets of appointment types to patients. Then, we jointly study the pricing and the capacity allocation decisions and show that the inclusion of the pricing decisions in the model simplifies the resulting optimization problem significantly. For example, when the pricing decisions are also included in the model, it is optimal to offer the same set of appointment types to all patients.

In the healthcare context, decision-making patients are frequently modeled as strategic patients in queues rather than patients who make a choice based on a discrete choice model. Tunçalp et al. (2024) consider strategic patients who decide to walk-in or make an appointment according to the endogenous rejection probability of walk-ins. Similarly, Rajan et al. (2019) and Zhou et al. (2023) model the telemedicine and in-person channels as queues where patients are strategic, and they study pricing and capacity (service rate) decisions. In Rajan et al. (2019), the main driver of telemedicine choice is the avoidance of a heterogeneous transportation cost in the in-person channel. Zhou et al. (2023) consider a pandemic setting with an infection risk. In their model, the disutility arising from the risk of getting infected at the clinic is not endogenously defined by the patients' choices but determined by an exogenous effort exerted by the clinic. Liu and Armony (2024) study the impact of offering telemedicine on the total expected reward of the provider and the total expected utility of the patients, and show that the benefit of telemedicine depends on the quality of the telemedicine service (measured in follow-up probability after telemedicine) and the provider's capacity mismatch relative to patient demand. Zhang et al. (2025) study a healthcare supply chain setting where a physical hospital shares its medical capacity with a telehealth platform in exchange for revenue. They compare the performances of a capacity-based contract (revenue-sharing based on received capacity) versus a volume-based contract (revenue-sharing based on served demand) in coordinating the supply chain and their impact on optimal decisions of channel choice, pricing, and reimbursement rate. Çakıcı and Mills (2025) analyze the impact of reimbursement strategies on capacity allocation decisions and channel choices. They show that pay parity (equal reimbursement of telemedicine and in-person channels) can lead to a decrease in patient access. They offer a value-based payment system where telemedicine's reimbursement rate gets closer to pay parity as its quality increases. Deshpande et al. (2022) consider capacity allocation between an emergency department (ED) and a clinic during a pandemic. Low-severity patients are directly routed to telemedicine. Patients with medium or high severity are either directed to the ED or offered an appointment at the clinic. The patient decides to enter a facility (ED or clinic) or not, where the endogeneity of patient choice comes from waiting times. Hassin et al. (2023) study a queueing model that includes an endogenous network effect through a customer loss function, which has three components, namely, the waiting time in the queue, the number of customers met while waiting in the queue, and the exposure time. They study customer behavior in terms of joining or balking and reneging from a queue in the presence of such a loss function.

In our choice model, the negative network effect is driven by an infection risk. In the operations management literature, there are recent papers considering epidemiological models that focus on the infection spread among agents (Kaplan 2020, Bertsimas et al. 2021, Fattahi et al. 2023). We do not consider the spread of the infection, but model an aggregate-level relationship between the patient density in the in-person channel and the risk of infection. A stream of papers studies capacity planning models in the presence of social distancing. Perlman and Yechiali (2020) estimate a customer's mean risk of infection and state that it is proportional to the number of customers occupying the space during the shopping route. Bozkir et al. (2021) schedule patients of different categories (uninfected, suspected, and infected) and minimize overlaps between different patient categories in the same unit to mitigate infection risk. Otten et al. (2023) study scheduling of in-person consultations while considering the waiting area capacity and meeting the social distancing guidelines. Bai et al. (2024) study public health policies considering trade-offs in social distancing versus lockdown. In their model, individuals' decisions to stay home or go out are a function of infection risk, resulting in an endogenous network effect. None of these papers considers telemedicine.

2.3 *Informational Interventions in Healthcare*

Behavioral operations management provides various research opportunities for scholars to improve processes by influencing behavioral tendencies or nudging actions (Donohue et al. 2020). The informational interventions that we study in Section 4 are in the form of nudge messages that underline a certain aspect of the in-person or telemedicine channel. Thaler and Sunstein (2008) define nudge as a mechanism that predictably changes people's behavior without prohibiting any option or significantly changing economic incentives. Nudges that frame information and change default options are frequently preferred by physicians and show promise in improving patients' clinical decision-making (Last et al. 2021). On patient engagement and access to care, simple reminder text message nudges can be effective (Liang et al. 2022). Reminding patients that they have a reserved COVID-19 vaccine to be shot at their next doctor's appointment is effective in increasing vaccination uptake (Milkman et al. 2021). Nudging patients by underlining the wait time for the next available appointment in case of missing the current appointment decreases no-shows (Liu and KC 2023). Showing an emotional video about the consequences of delaying needed care for eye treatment on a patient's health and personal life significantly increases the on-time arrivals of patients for their first follow-up appointments. Conversely, showing a technical video that explains the disease and the treatment has no significant impact on timely follow-up rates (Çamlıbel et al. 2025). The default nudge that offers a predefined channel choice for the patients has an impact on the final channel choice (Schmidtke et al. 2022). When the default option is video, 65% of patients choose that option, while for the active choice and in-person default, the percentage of telemedicine choosers decreases to 41% and 25%, respectively. The study by González and Scartascini (2024) is closest to our work as they test the effectiveness of an informational intervention in nudging patients to increase telemedicine use in the presence of an infection risk. They sent emails to patients that contain information about the benefits of using a telemedicine application and instructions on how to use it. They found a significant increase in telemedicine adoption after their message intervention. Different than their study that focuses only on telemedicine use, our setting offers an active choice between telemedicine and in-person channels. Our experimental setting also allows for testing the effectiveness of messages that differ in framing (positive or negative) and infection risk focus (self-risk only or self-risk and risk for others). Our study contributes to the patient channel choice management literature by testing the effectiveness of different messages on telemedicine use during epidemics and respiratory virus seasons.

Chapter 3

CAPACITY ALLOCATION AND PRICING UNDER CONTAGION-AWARE PATIENT CHOICE

This chapter formulates an optimization model that provides optimal capacity allocation and pricing decisions, maximizing a healthcare provider's revenue. It shows the importance of the telemedicine channel in mitigating revenue losses during epidemics. It considers several further aspects, including physician sickness, welfare maximization, management of patients' contagion awareness levels, and partial effectiveness of the telemedicine channel, resulting in in-person revisits.

3.1 Model Specification under Fixed Prices

This section presents the capacity allocation model between the telemedicine and in-person channels that maximizes revenue. The prices of the channels are fixed. Patients' appointment choices are affected by their contagion awareness, which is driven by the fear of contracting the disease in the healthcare setting.

3.1.1 Patient Choice with Contagion Awareness

Patient channel choice is modeled as a discrete choice with options of telemedicine, in-person, and no appointment. The intrinsic values and costs of appointments determine the patient's utility for the channels. V_t and V_i represent the intrinsic valuations of the patients for the telemedicine and in-person channels. V_i includes a homogeneous cost of transportation. Without loss of generality, the valuation of not choosing an appointment is assumed to be zero. p_t and p_i represent the price of the telemedicine and the in-person channels, whereas a_t and a_i represent the coinsurance rates. A patient choosing the telemedicine (in-person) channel pays

$a_t \in (0,1]$ ($a_i \in (0,1]$) fraction of the price while the rest, which is equal to $(1-a_t)p_t$ ($(1-a_i)p_i$), is paid by her insurance.

In the utility of the in-person channel, there is a disutility term associated with visiting the healthcare provider, driven by a contagion function, $R(\cdot)$. The fixed capacity of the healthcare provider causes an increase in the density of the patients in a given area, such as a waiting room, when there is an increase in the in-person demand. This density increase reduces the possibility of conforming to the social distancing rules, which further increases the risk of contagion due to increased exposure of the patients to each other. Garcia et al. (2021) also suggest that density is the main factor that influences the infection rate within a moving crowd. Similarly, Goscé et al. (2014) show the effect of crowd density on the rate of infection and walking speed in a confined space. They argue that as the density of the crowd increases, walking speed decreases. Consequently, people spend more time in a given area, increasing the infection rate. Studies are showing that breathing and talking produce droplets, and these aerosolized particles of SARS-CoV-1 and SARS-CoV-2 can remain in the air for hours (Anderson et al. 2020). This implies that a patient who takes a later-day appointment can still be exposed to the particles dropped by a patient who has already left the healthcare facility. Then, the patient volume matters for all upcoming patients, even when they have different appointment slots. We allow the contagion function to start from a strictly positive value ($R(0) > 0$), both to capture the contagion risk through aerosols in the air and also via healthcare workers who may themselves be infected from cumulative patient contact. Based on these observations, the contagion function, $R(\lambda_i)$, is a non-decreasing function of the number of in-person appointments in a particular booking horizon, λ_i, making it endogenous. More explicitly, as the probability of choosing the in-person channel increases, the in-person demand will also increase, which will increase the contagion. This increase in the contagion will decrease the probability of choosing the in-person channel for the upcoming choices. Then, the in-person demand will decrease, which will decrease the contagion and increase the probability of an in-person channel choice once more. Since this endogenous contagion impact is updated according to the choices of the patients, our model aims to determine the equilibrium number of in-person demand, which is consistent with the rational expectations equilibrium.

$R(\lambda_i)$ is multiplied by $r \in [0, 1]$, contagion awareness, which models how patients reflect the contagion function into their channel choice. Consequently, $rR(\lambda_i)$ gives the overall contagion effect. The parameter r is driven by awareness and fear of contagion, which are the main reasons behind the avoidance of seeking needed care. The behavior of delaying needed care during the COVID-19 pandemic is mainly driven by the patient's fear of catching the infection at the clinics (Wong et al. 2020). Within an Italian Pediatric Hospital Research Network, a decrease in pediatric emergency department visits is attributed to patients avoiding accessing the hospital due to fear of catching COVID-19 (Lazzerini et al. 2020a). Patients anticipate the relationship between increased volume and shortages in personal protective equipment, an increase in waiting times, and their risk of infection (Wong et al. 2020). These observations underline the impact of infection fear on patient demand for in-person visits.

The utilities for telemedicine and in-person channels, and not choosing an appointment (outside option) are formulated as follows,

$$U_t = V_t - a_t p_t + \epsilon_t, \;\; U_i = V_i - a_i p_i - rR(\lambda_i) + \epsilon_i, \;\; U_o = \epsilon_o,$$

where ϵ_t and ϵ_i are independent standard Gumbel random variables. Once the utilities are determined, the choice probabilities are calculated according to the Multinomial Logit (MNL) model (McFadden 1974). This model is widely used in the healthcare literature (Feldman et al. 2014, Wang and Fung 2015, Bai et al. 2024). Under the MNL model, given that both options are offered to a patient, the probabilities of choosing a telemedicine appointment and choosing an in-person appointment are

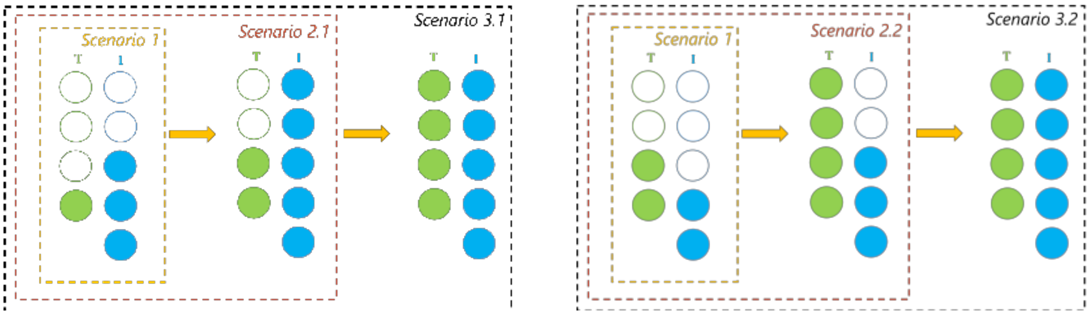
$$\frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(\lambda_i)}},$$
$$\frac{e^{V_i - a_i p_i - rR(\lambda_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(\lambda_i)}},$$

respectively.

We assume that patients know the number of in-person appointments and the contagion function, and thus, they know the contagion effect, $rR(\lambda_i)$. The number of in-person appointments can be estimated by the patient's own experience, word of mouth, or by the observation of occupied slots from an online booking system. Daily news containing statistics like the number of cases, the number of hospitalized patients, and the number of patients on ventilators is available to the patients. There is also information about the healthcare center, such as the structure of the waiting area and the precautions taken by the management (hygiene or social distancing rules). The type of examination, whether it allows the patient to use a mask or not, may also have an impact on the contagion effect. Goolsbee and Syverson (2021) show that consumer traffic in stores is affected by the number of reported COVID-19 deaths, and there is a shift in traffic in favor of less busy stores. Gale et al. (2021) investigate the importance of several factors in the decision of seeking emergency department (ED) care during the initial peak of the pandemic. These factors are reducing the chance of dying by having an ED treatment, the crowdedness of the ED, and the chance of contracting COVID-19 in the ED. They find that, under the myocardial infarction scenario, which has a 40% risk of death without treatment, the mean importance scores are 53.4%, 25%, and 21.6%, respectively. Under appendicitis (4% risk of death without treatment), those numbers are 36.6%, 33.3%, and 30.1%, respectively. This provides empirical support for our claim that patients consider crowd density and risk of infection in their decisions of seeking care.

3.1.2 Allocating Capacity between the Channels

A deterministic fluid model is considered in which the mass of patients using the appointment system in a given time horizon is equal to λ (potential demand), where the parameter $\lambda > 0$. The patients are assumed to be infinitesimally small to obtain a fluid model. The provider decides on the capacities of telemedicine and in-person channels for a particular booking horizon. It is assumed that all patients get an appointment prior to their treatment (no walk-ins). All patients are assumed to show



(a) in-person is fully reserved first (b) telemedicine is fully reserved first

Figure 3.1: Illustration of different demand fulfillment scenarios: (left) in-person capacity is fully reserved first, (right) telemedicine capacity is fully reserved first.

up for their appointments. Patients' preferences are homogeneous, meaning they choose according to the same utilities for a given appointment type. Telemedicine appointments refer to real-time video consultations, which are assumed to be perfect substitutes for in-person appointments. In Section 3.4.4, the perfect substitutability assumption is relaxed. The costs of the channels for the provider are assumed not to differ significantly (Portney et al. 2020, Snoswell et al. 2020), and thus, the focus is on revenue maximization rather than profit maximization. This is extended in Section 3.4.2, where we also analyze the objective of welfare maximization. In the revenue maximization objective, the effect of contagion is only considered by the patients in their utility. However, in welfare maximization, in addition to the revenue, the provider also considers the effect of contagion on the patients' utilities in its objective.

The total capacity of the provider, $C > 0$, is fixed and represents the total duration of the service provided by fully flexible doctors who can offer both appointment types. The main decision variables, C_t and C_i, represent the capacities dedicated to telemedicine and in-person appointments. The number of booked appointments for the telemedicine and in-person channels is denoted by λ_t and λ_i. The durations of the telemedicine and the in-person appointments are denoted by m_t and m_i.

In the capacity allocation problem, after one of the channel types, telemedicine or in-person, is fully occupied, the choice set is updated accordingly. Figure 3.1 illustrates the problem where T represents the telemedicine channel and I represents the in-person channel. In both (a) and (b), Scenario 1 represents the case in which the provider offers both types of channels to all patients. If both channels are offered initially, yet the total capacity is not enough to meet all the demand, then at least one of the channel types is fully reserved. Consequently, after a certain time, only one channel type is offered, which is represented by Scenarios 2.1 and 2.2, where in (a) only the telemedicine channel and in (b) only the in-person channel is offered to some patients. Scenarios 3.1 and 3.2 represent the case where both channels are fully reserved, where in (a) the in-person channel is fully reserved before the telemedicine channel, and in (b) the telemedicine channel is fully reserved before the in-person channel. Another possible scenario is that both channels are fully occupied at the same time, so that for the rest of the booking horizon, no channel type is offered to the upcoming patients. Finally, it is possible to offer a single channel type from the beginning, that is, it is possible to offer only the in-person or only the telemedicine channel during the whole booking horizon. Our model covers all these possible demand fulfillment scenarios, which are explained in detail after the presentation of the related optimization problem.

The capacity allocation problem is as follows.

$$\max_{\substack{\lambda_t,\lambda_i,C_t,C_i,\theta,\alpha,\beta,\\ x_1,y_1,y_2}} \quad p_t\lambda_t + p_i\lambda_i \tag{3.1a}$$

$$\text{s.t.} \quad x_1 = \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(\lambda_i)}} \tag{3.1b}$$

$$x_2 = \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t}} \tag{3.1c}$$

$$y_1 = \frac{e^{V_i - a_i p_i - rR(\lambda_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(\lambda_i)}} \tag{3.1d}$$

$$y_2 = \frac{e^{V_i - a_i p_i - rR(\lambda_i)}}{1 + e^{V_i - a_i p_i - rR(\lambda_i)}} \tag{3.1e}$$

$$\lambda\left(\theta\left(\alpha x_1 + (1-\alpha)\beta x_2\right) + (1-\theta)\left(\alpha x_1\right)\right) = \lambda_t \tag{3.1f}$$

$$\lambda_t \leq C_t \tag{3.1g}$$

$$\lambda\left(\theta\left(\alpha y_1\right) + (1-\theta)\left(\alpha y_1 + (1-\alpha)\beta y_2\right)\right) = \lambda_i \tag{3.1h}$$

$$\lambda_i \leq C_i \tag{3.1i}$$

$$m_t C_t + m_i C_i \leq C \tag{3.1j}$$

$$\lambda_t, \lambda_i, C_t, C_i \geq 0 \tag{3.1k}$$

$$x_1, y_1, y_2, \alpha, \beta \in [0,1] \tag{3.1l}$$

$$\theta \in \{0,1\}. \tag{3.1m}$$

(3.1a) represents the revenue maximization objective. (3.1b)−(3.1e) are the constraints determining the channel choice probabilities under different scenarios where x_1, y_1, and y_2 are decision variables, and x_2 is a parameter. (3.1f)−(3.1j) are the constraints allocating the capacity to the channels. x_1 represents the telemedicine choice probability when both channels are offered. x_2 is the telemedicine choice probability when only the telemedicine channel is offered. y_1 represents the in-person choice probability when both channels are offered. y_2 is the in-person choice probability when only the in-person channel is offered. θ is the binary decision variable that determines either which channel type is fully occupied first (if both channels are offered initially) or which channel type is the one that is offered (if a single channel type is offered from the beginning). If $\theta = 0$ ($\theta = 1$), the telemedicine channel (the in-person channel) is fully occupied first or not offered from the beginning. If

$\theta \in \{0, 1\}$, then either both channels are offered to all patients, or both channels are fully occupied at the same time. α represents the fraction of patients that are offered both channel types and $(1-\alpha)\beta$ represents the fraction of patients that are offered a single channel (either telemedicine or in-person). If $\alpha < 1$ and $\beta < 1$, a fraction of patients are not offered any channel at all (rejected). The formal definitions of the scenarios based on the decision variables (θ, α, β) are presented below. The optimization problem is nonlinear and nonconvex. That increases the complexity of the proofs in our theoretical results. For the numerical analyses, we take two subproblems by assigning either $\theta = 0$ or $\theta = 1$ to eliminate the integer variable. We use MATLAB's fmincon function to solve each subproblem. To improve the robustness of the solution and address potential local optima, a MultiStart approach is applied with 500 randomly selected initial points. The feasible subproblem with the higher objective function value is chosen as the final output.

The optimization problem (3.1) always has a feasible solution. A trivial feasible solution is obtained if we set $\theta = \alpha = \beta = 0$. Then, we have $\lambda_t = \lambda_i = 0$ and (x_1, y_1, y_2) are determined by the constraints (3.1b), (3.1d), and (3.1e). The following lemma simplifies the notation.

Lemma 1 *Without loss of optimality, we can replace the less than or equal to signs in the constraints* (3.1g) *and* (3.1i) *with equality signs. In other words, setting* $\lambda_t = C_t$ *and* $\lambda_i = C_i$ *in the optimization problem* (3.1) *does not decrease the optimal objective function value. Furthermore, this result is valid under any objective function that is not a function of* C_t *or* C_i.

The proof of Lemma 1 is presented in Appendix A. By Lemma 1, we will use the notation (C_t, C_i) instead of (λ_t, λ_i) henceforth. Consequently, we use $R(C_i)$, rather than $R(\lambda_i)$, to denote the contagion function. The list of scenarios, depending on the values of θ, α, and β are as follows.

Scenario 1 *Let* $\theta = \{0, 1\}$, $\alpha = 1$, *and* $\beta \in [0, 1]$. *Then, all patients are offered both channel types.*

Scenario 2.1 *Let* $\theta = 1$, $\alpha \in (0, 1)$, *and* $\beta = 1$. *Then,* α *fraction of patients* *are offered both channel types, and $1 - \alpha$ fraction of patients are offered only the telemedicine channel.*

Scenario 2.2 *Let $\theta = 0$, $\alpha \in (0, 1)$, and $\beta = 1$. Then, α fraction of patients are offered both channel types, and $1 - \alpha$ fraction of patients are offered only the in-person channel.*

Scenario 3.1 *Let $\theta = 1$ and α, $\beta \in (0, 1)$. Then, α fraction of patients are offered both channel types. $(1 - \alpha)\beta$ fraction of patients are offered only the telemedicine channel. And, $1 - \alpha - (1 - \alpha)\beta$ fraction of patients are not offered any appointment.*

Scenario 3.2 *Let $\theta = 0$ and α, $\beta \in (0, 1)$. Then, α fraction of patients are offered both channel types. $(1 - \alpha)\beta$ fraction of patients are offered only the in-person channel. And, $1 - \alpha - (1 - \alpha)\beta$ fraction of patients are not offered any appointment.*

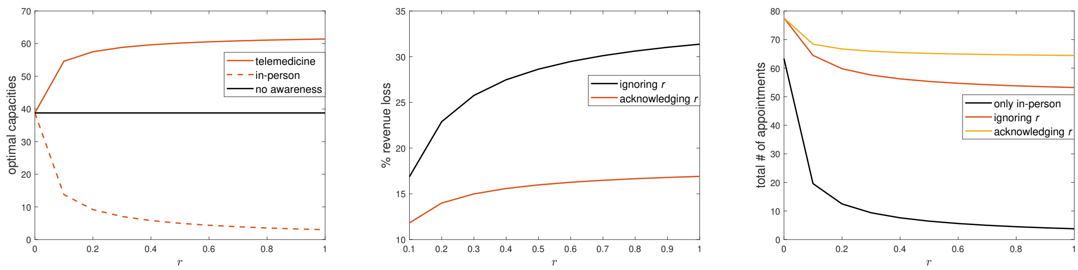
Scenario 4 *Let $\theta = \{0, 1\}$, $\alpha \in (0, 1)$, and $\beta = 0$. Then, α fraction of patients are offered both channel types, and $1 - \alpha$ fraction of patients are not offered any appointment.*

Scenario 5.1 *Let $\theta = 1$, $\alpha = 0$, and $\beta \in [0, 1]$. Then, β fraction of patients are offered only the telemedicine channel while the in-person channel is not offered at all.*

Scenario 5.2 *Let $\theta = 0$, $\alpha = 0$, and $\beta \in [0, 1]$. Then, β fraction of patients are offered only the in-person channel while the telemedicine channel is not offered at all.*

3.2 The Effect of Contagion on the Revenue Loss

This section explores the effect of contagion on the patient choice and the provider's revenue loss. We illustrate that contagion awareness affects the optimal capacities to allocate to in-person and telemedicine channels, the revenue loss due to an epidemic, and the total number of appointments (access). Some of the revenue loss can be eliminated by our model that takes the contagion-awareness into account



(a) capacities (b) revenue loss (c) access

Figure 3.2: Changes in (a) the optimal capacity allocation, (b) the revenue loss, and (c) the total number of appointments as the contagion awareness parameter, r, increases under the parameter set: $C = \lambda = 100$, $R(C_i) = C_i$, $V_t = V_i = 5$, $m_t = m_i = 1$, $a_t = a_i = 1$, $p_t = p_i = 4.45$, $r \in \{0, 0.1, 0.2, ..., 1\}$.

when allocating capacities. We prove that the number of in-person appointments decreases significantly due to the contagion effect, which results in a significant revenue loss. Finally, we present examples of convex (squared) and concave (square-rooted) contagion functions to illustrate the effects of the contagion function on the provider revenue and the number of no-bookings (outside options) as utilities of the telemedicine and the in-person channels change.

Figure 3.2 illustrates a case in which the optimal revenue is achieved under Scenario 1, where the healthcare provider offers both telemedicine and in-person channels to all patients. The prices are fixed to the optimal prices when the contagion awareness is ignored (in Section 3.3, we optimize the prices while acknowledging the contagion awareness). In Figure 3.2a, the black line indicates the optimal capacity allocated to both channel types when the contagion awareness is ignored. In that case, because $V_t - a_t p_t = V_i - a_i p_i$, both channels are assigned equal capacity. When the contagion awareness, r, is considered, as it increases, the optimal telemedicine capacity increases, whereas the optimal in-person capacity decreases. This is in line with the empirical observations that report the negative effect of the pandemic on in-person visits for various illnesses (Rubin 2020, Moynihan et al. 2021, Stephenson et al. 2021). Notice that the optimal capacities do not add up to $C = 100$ because some patients choose the outside option. Figure 3.2b presents the revenue loss with respect to the optimal revenue when there is no contagion awareness (that is, the optimal revenue when $r = 0$) under two different capacity allocation decisions. Under the first decision, the healthcare provider ignores the contagion awareness of the patients and equally splits the capacity, that is, $C_t = C_i = 50$ even though $r > 0$. The revenue loss due to ignoring contagion awareness reaches up to 31% as $r \uparrow 1$. Under the second decision, the healthcare provider uses an optimal solution to the optimization problem (3.1), and thus the contagion awareness of the patients is taken into account. The revenue loss due to the existence of contagion awareness reaches up to 17% as $r \uparrow 1$. In summary, the revenue loss due to ignoring the contagion awareness of the patients is significant. Although acknowledging the contagion awareness of the patients decreases the revenue loss significantly (from 31% to 17%), the revenue loss due to the existence of contagion awareness is still significant (17%). Finally, in Figure 3.2c, we see that acknowledging contagion awareness in capacity allocation decisions increases the total number of appointments (access) compared to ignoring it. When telemedicine is not offered, access decreases significantly.

The following theorem formalizes our observations from Figure 3.2. Let $\pi^R(\lambda)$ and $\pi^{NR}(\lambda)$ denote the revenue as a function of the potential demand λ under the contagion effect and no contagion, respectively. Let $O(\cdot)$ denote the Big-O notation: $f = O(g)$ means that there exist $k, n_0 > 0$ such that if $n \geq n_0$, then $|f(n)| \leq kg(n)$. Let $\Theta(\cdot)$ denote the Big-Theta notation: $f = \Theta(g)$ means that there exists $k_1, k_2, n_0 > 0$ such that if $n \geq n_0$, then $k_1 g(n) \leq f(n) \leq k_2 g(n)$.

Theorem 1 *Suppose that $C = +\infty$, that is, the capacity is abundant. Suppose also that*

$$p_i > p_t \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t}} > 0. \tag{3.2}$$

(1.1) Suppose that $r = 0$ or $R(s) = 0$ for all $s \geq 0$, that is, there is no contagion. Then, it is optimal to offer in-person appointments to all patients. Furthermore, $C_i(\lambda) = \Theta(\lambda)$, $C_t(\lambda) = O(\lambda)$, and $\pi^{NR}(\lambda) = \Theta(\lambda)$.

(1.2) Suppose that $r \in (0,1]$ and $R(s) = b_0 + b_1 s^{b_2}$ for all $s \geq 0$, where $b_0 \geq 0$ and $b_1, b_2 > 0$ are arbitrary constants, that is, the contagion effect is a polynomial with degree b_2.

(1.2.i) If both options are offered to all patients, then $C_i(\lambda) = \Theta((\ln(\lambda))^{1/b_2})$, $C_t(\lambda) = \Theta(\lambda)$, and $\pi^R(\lambda) = \Theta(\lambda)$.

(1.2.ii) If only in-person appointments are offered to all patients, then $C_i(\lambda) = \Theta((\ln(\lambda))^{1/b_2})$ and $\pi^R(\lambda) = \Theta((\ln(\lambda))^{1/b_2})$.

(1.2.iii) If only telemedicine appointments are offered to all patients, then $C_t(\lambda) = \Theta(\lambda)$ and $\pi^R(\lambda) = \Theta(\lambda)$.

In each of the cases (1.2.i), (1.2.ii), and (1.2.iii), we have $\pi^{NR}(\lambda) - \pi^R(\lambda) = \Theta(\lambda)$, that is, the revenue loss due to the contagion effect is significant.

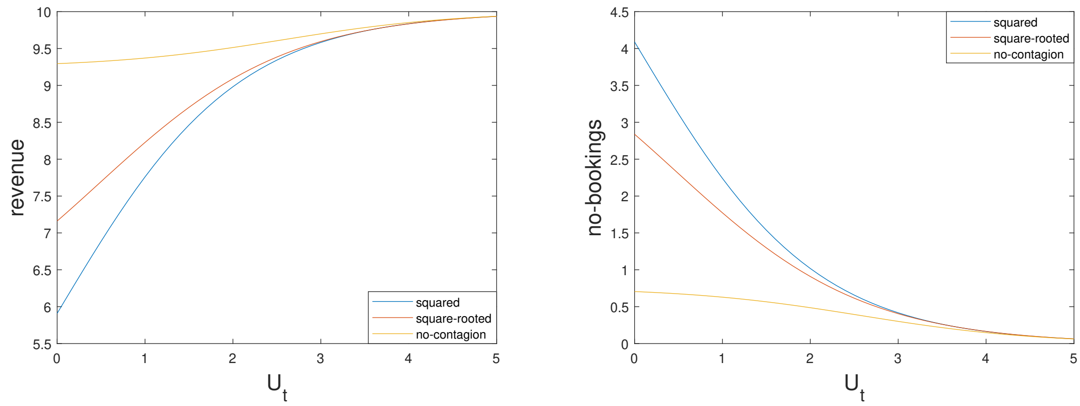
The proof of Theorem 1 is presented in Appendix C. Condition (3.2) ensures that the price of in-person appointments is sufficiently large so that it is optimal to offer in-person appointments to the patients when there is no contagion effect. That allows us to have a nontrivial capacity allocation problem.

Theorem 1 states that if there is no contagion effect, the number of in-person appointments is $\Theta(\lambda)$; whereas, if there is a contagion effect, it is $\Theta((\ln(\lambda))^{1/b_2})$. Therefore, the existence of the contagion effect decreases the order of the number of in-person appointments significantly. When telemedicine is offered, the revenue increases linearly in λ. However, if telemedicine is not offered, the revenue increases logarithmically in λ. Therefore, under the contagion effect, offering telemedicine appointments to patients prevents a decrease in the order of revenue. In other words, telemedicine appointments are a valuable source of revenue under the contagion effect. Theorem 1 explains the component of the healthcare revenue losses driven by the low patient volumes due to COVID-19 in 2020 (American Hospital Association 2020). The theorem shows the critical role of the telemedicine channel in providing enhanced healthcare access during epidemics.

The contagion function in our model is a non-decreasing function of the number of in-person appointments, which allows for taking different functions into account.

As more patients choose the in-person channel, not only will the proximity of the patients in the waiting area increase, but there will also be a greater chance of a longer time spent within the area. There is another source of risk, which is the cumulative virus exposure of the healthcare workers as they spend hours in a given area and come into contact with an increasing number of patients. Those factors imply a potentially non-linear contagion function that can be affected by risk mitigation measures such as social distancing rules, frequent cleaning, effective use of masks, and vaccination. This would be captured by a different contagion function in our model. To see how the number of no-bookings (outside options) and consequently the revenue changes for varying contagion functions under different utility values of the telemedicine appointments, Figure 3.3 is presented, where $R(C_i) = (C_i)^{b_2}$ under Scenario 1. For the no-contagion case, we take $r = 0$. For the square-rooted and the squared contagion cases, $r = 1$. $U_t = V_t - a_t p_t$ is the telemedicine utility, and $W_i = V_i - a_i p_i$ is the in-person utility without the contagion effect. We have $p_t = p_i = 1$ and thus, the revenue is the sum of the capacities. The values of b_2 for the square-rooted and the squared contagion functions are 0.5 and 2, respectively. A squared contagion function represents the case in which the same number of in-person appointments leads to a higher contagion effect than the square-rooted contagion function. In (a), we observe the role of the contagion function on the revenue loss. We see a larger revenue gap under a squared contagion function compared to a square-rooted contagion function. Another observation from (a) is that the revenue gap is larger at smaller values of U_t, for which the telemedicine channel is preferred less. As Theorem 1 suggests, because of the contagion effect, the in-person demand increases logarithmically with the potential demand. That would imply that, because of $R(C_i)$, an increase in W_i would not have the same effect in terms of revenue as an increase in U_t.

There are three options offered to the patients in the choice set: booking an in-person appointment, booking a telemedicine appointment, or an outside option (no booking). When the prices are equal, switching between in-person and telemedicine appointments does not change the revenue. The only effect on the revenue is the



(a) revenue (b) outside option

Figure 3.3: Changes in (a) revenue and (b) no-bookings (outside options) for no-contagion, squared contagion, and square-rooted contagion under $U_t \in \{0, 0.1, 0.2, ..., 5\}$ and $W_i = 2.5$, $\lambda = 10$

change in the rate of no-bookings. In Figure 3.3 (b), the change in the number of no-bookings is presented under the same setting as Figure 3.3 (a). We see the highest no-bookings under the squared contagion function for small values of U_t, which supports the previous analysis of revenues.

In summary, we see that patients' choice behavior in terms of telemedicine and in-person choice probabilities changes with the existence of a contagion effect, which further affects provider revenue. The provider needs to consider the effect of contagion on the capacity allocation decisions to maximize its revenue. Next, we consider the joint optimization of capacity allocation and pricing for the two channels.

3.3 Model Specification under Optimal Prices

In this section, we study the case in which the prices of the telemedicine and in-person appointments, (p_t, p_i), are decision variables in the optimization problem (3.1). When the prices are parameters, the previous section shows that there is a significant revenue loss under the contagion effect. In this section, we show that even under optimal prices, there is still a significant revenue loss under the contagion effect.

When the prices are decision variables, it does not make sense not to offer any appointments to a patient. Intuitively, if the potential demand is high, the healthcare provider can decrease the demand by increasing the prices, and thus, not offering any appointments to a patient is suboptimal. Consequently, when the prices are decision variables and the contagion effect is polynomial, the optimization problem (3.1), which is a nonlinear mixed-integer optimization problem, simplifies into a convex optimization problem.

Theorem 2 *Suppose that the prices are also decision variables in the optimization problem* (3.1)*. Then, an optimal solution to the following optimization problem provides optimal capacity allocation and prices for the optimization problem* (3.1)*:*

$$\max_{C_t,C_i} \frac{C_t}{a_t}\Big(V_t - \ln\big(C_t\big) + \ln\big(\lambda - C_t - C_i\big)\Big)$$
$$+ \frac{C_i}{a_i}\Big(V_i - rR\big(C_i\big) - \ln\big(C_i\big) + \ln\big(\lambda - C_t - C_i\big)\Big) \tag{3.3a}$$
$$s.t.\ m_t C_t + m_i C_i \le C \tag{3.3b}$$
$$C_t + C_i \le \lambda \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \tag{3.3c}$$
$$C_t, C_i \ge 0. \tag{3.3d}$$

Let (C_t^*, C_i^*) *be an optimal solution, which always exists. Then, the optimal prices are as follows,*

$$p_t^* = \frac{1}{a_t}\Big(V_t - \ln\left(C_t^*\right) + \ln\left(\lambda - C_t^* - C_i^*\right)\Big),$$
$$p_i^* = \frac{1}{a_i}\Big(V_i - rR\left(C_i^*\right) - \ln\left(C_i^*\right) + \ln\left(\lambda - C_t^* - C_i^*\right)\Big).$$

Finally, if $R(s) = b_0 + b_1 s^{b_2}$ *for all* $s \ge 0$ *where* $b_0 \ge 0$ *and* $b_1, b_2 > 0$ *are arbitrary constants, the objective function becomes strictly concave, and thus* (3.3) *becomes a convex optimization problem.*

The proof of Theorem 2 is presented in the Appendix D. Once the optimal capacities, C_t^* and C_i^*, are found, the corresponding optimal prices of p_t^* and p_i^* can be calculated easily due to the one-to-one relationship between the prices and the capacities. For mathematical completeness, we assume that $0 \times \infty := 0$ to cover the case in which $\min\{C_t, C_i\} = 0$. In other words, the optimization problem (3.3) accounts for the case of offering only one appointment type during the whole booking horizon. For example, if only in-person appointments are offered, that is, if $C_t = 0$, then the objective function (3.3a) becomes equal to $(C_i/a_i)(V_i - rR(C_i) - \ln(C_i) + \ln(\lambda - C_t - C_i))$.

Observe that (3.3) is very similar to the optimization problem (P0) of Du et al. (2016) and the optimal prices in Theorem 2 resemble the ones in that paper. This shows that some of the results in Du et al. (2016), which focus on a positive externality, are maintained under a negative network effect and a finite service capacity/product inventory setting.

Because (3.3) is a convex optimization problem under the polynomial contagion effect, if the unique maximizer of the objective function (3.3a) satisfies the constraints (3.3b), (3.3c), and (3.3d), then it is the optimal solution to (3.3). This observation leads to the following result, which is proven in the Appendix E.

Theorem 3 *Suppose that the contagion function is polynomial such that* $R(s) = b_0 + b_1 s^{b_2}$ *for all* $s \geq 0$*, where* $b_1, b_2 > 0$*,* $b_0 \geq 0$*, and the coinsurance rates of the telemedicine and the in-person appointments are the same, that is,* $a_i = a_t = a$ *where* $a \in (0, 1]$*. Suppose also that,*

$$\lambda \max\{m_t, m_i\} \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \leq C. \tag{3.4}$$

Let (C_i^*, C_t^*) *be the optimal capacity allocation and* (p_i^*, p_t^*) *be the corresponding optimal prices. Then,*

$$p_i^* - p_t^* = \frac{1}{a} r b_1 b_2 \left(C_i^*\right)^{b_2} \geq 0. \tag{3.5}$$

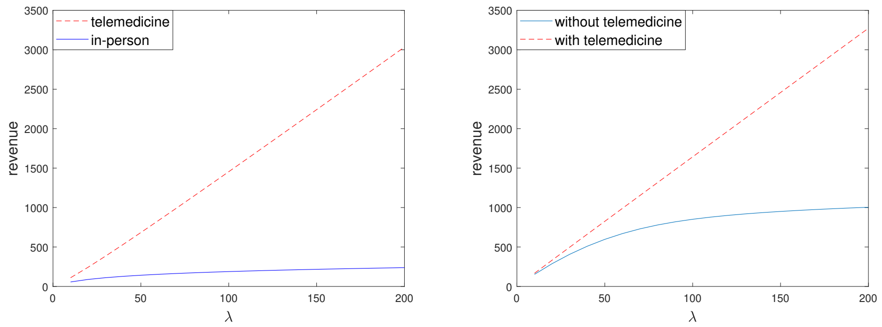
Furthermore, C_t^*/C_i^* *and* $p_i^* - p_t^*$ *are strictly increasing in* r*, that is, the optimal capacity ratio and the optimal price gap are strictly increasing in contagion awareness.*

The inequality in (3.4) ensures that the total capacity is enough to satisfy all the potential demand. The optimal price gap presented in (3.5) holds when the patients pay the same fraction of the price under telemedicine and in-person appointments, while the rest is covered by the insurance (that is, when $a_i = a_t = a$). This is consistent with Medicare, which offers equal coverage for many telehealth services (Centers for Medicare & Medicaid Services 2020). If the patients are not contagion-aware ($r = 0$), the optimal telemedicine and in-person appointment prices are the same ($p_i^* = p_t^*$). However, if the patients are contagion-aware ($r \in (0, 1]$), the optimal price gap is positive and strictly increases in contagion awareness. Then, the optimal solution is to keep telemedicine appointments more appealing than in-person appointments by charging a lower price for the telemedicine channel compared to the in-person channel.

In Theorem 1, we show that if the telemedicine and in-person appointment prices are fixed, the revenue loss due to the contagion awareness of the patients is significant. We investigate if the revenue loss is still significant when the prices are allowed to be optimized. Theorem 4 answers the aforementioned question affirmatively. In Theorem 4, we consider a sequence of systems indexed by n where $n \geq 1$. Specifically, in the nth system, we scale the potential demand and capacity with n and the contagion effect with $1/n$ so that the contagion function will not grow a lot as n increases. The superscript n implies that the corresponding parameter or variable belongs to the nth system.

Theorem 4 *Consider a sequence of systems indexed by n where $n \geq 1$. In the nth system, $\lambda^n := n\lambda$, $C^n := nC$, and $R^n(s) := b_0 + b_1(s/n)^{b_2}$, where $b_0 \geq 0$, $b_1, b_2 > 0$,* (3.4) *holds, and $a_i = a_t = a$ where $a \in (0, 1]$. In the nth system, let $\pi^{n,R}$ and $\pi^{n,NR}$ denote the optimal revenue under contagion effect* ($r \in (0, 1]$) *and no contagion effect* ($r = 0$)*, respectively. Then, we have $\pi^{n,NR} - \pi^{n,R} = \Theta(n)$.*

Theorem 4 states that under the optimal prices, the revenue loss due to the contagion awareness of the patients is of first order. The proof of Theorem 4 is presented in Appendix F. Figure 3.4 shows the change in the provider revenue as a function of the potential demand (λ) for the telemedicine and the no-telemedicine cases under optimal pricing. In (a), we observe that as λ increases, the revenue

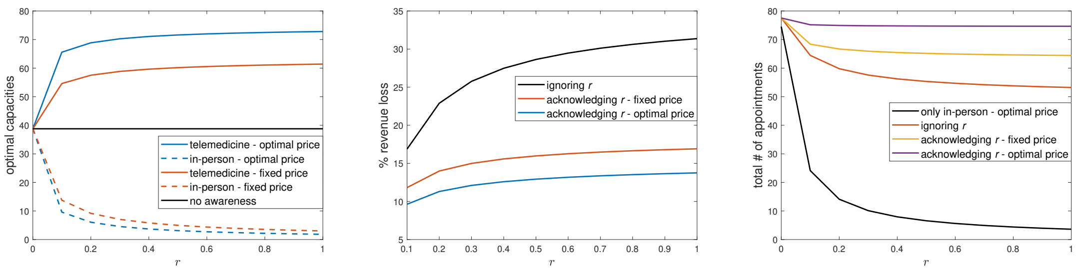


(a) revenue derived from the channels (b) total revenue with(out) telemedicine

Figure 3.4: Increase in revenue (a) from the two channels and (b) with and without telemedicine, with increasing potential demand λ, parameter set: $(V_i, V_t, C, r, b_0, b_1, b_2, a_t, a_i, m_t, m_i) = (20, 20, 200, 0.1, 0.5, 1, 1, 1, 1, 1, 1)$, $\lambda \in \{10, 20, 30, ..., 200\}$

derived from the telemedicine appointments increases linearly. In contrast, there is a logarithmic increase in the revenue derived from the in-person appointments due to the contagion effect. In (b), we compare the total revenue of the provider with and without the telemedicine service. Because of the tele-arrivals, revenue increases linearly when telemedicine is offered. If the provider only offers in-person appointments, its revenue has a logarithmic increase with an increase in λ. These observations illustrate the importance of offering telemedicine during epidemics.

Recall Figure 3.2b, which numerically depicts the revenue losses when the contagion awareness is ignored and acknowledged. In Figure 3.2, the prices are fixed to their optimal values when $r = 0$. Therefore, when $r > 0$, suboptimal prices are charged. In Figure 3.5, we present the numerical experiments in Figure 3.2 by also optimizing the prices as the contagion awareness parameter, r, changes. Specifically, Figure 3.5a is an extension of Figure 3.2a by also showing the optimal capacity allocation decisions under the optimal prices. When the prices are also optimized, the optimal solution assigns more capacity to the telemedicine channel and less capacity to the in-person channel compared to the optimal solution under the fixed



(a) capacities (b) revenue loss (c) access

Figure 3.5: Changes in (a) the optimal capacity allocation, (b) the revenue loss, and (c) the total number of appointments (access) as the contagion awareness parameter, r, increases under the parameter set: $C = \lambda = 100$, $R(C_i) = C_i$, $V_t = V_i = 5$, $m_t = m_i = 1$, $a_t = a_i = 1$, $r \in \{0, 0.1, 0.2, ..., 1\}$ and under the fixed ($p_t = p_i = 4.45$) and optimal prices.

prices. This is accomplished by increasing the in-person appointment price while decreasing the telemedicine appointment price as r increases (recall Theorem 3). In other words, as the patients become more contagion-aware, the optimal solution is to make the telemedicine (in-person) channel more (less) appealing by decreasing (increasing) its price. Figure 3.5b is an extension of Figure 3.2b by also showing the revenue loss due to the existence of contagion awareness under the optimal prices. Let us focus on the case where $r = 1$. When the contagion awareness is ignored, the revenue loss is 31%. When it is acknowledged but the prices are kept fixed, the revenue loss is 17%. When the prices are also optimized, the revenue loss is 14%. In healthcare systems where providers can control prices in addition to capacities, we see that pricing is a valuable control in decreasing revenue losses. Finally, in Figure 3.5c, we see the positive impact of optimizing prices on the total number of appointments (access). The benefit of offering telemedicine in patient access is still significant under optimal pricing.

In the next section, we analyze several features that affect channel decisions of the provider and the patients.

3.4 Further Features Affecting Channel Decisions

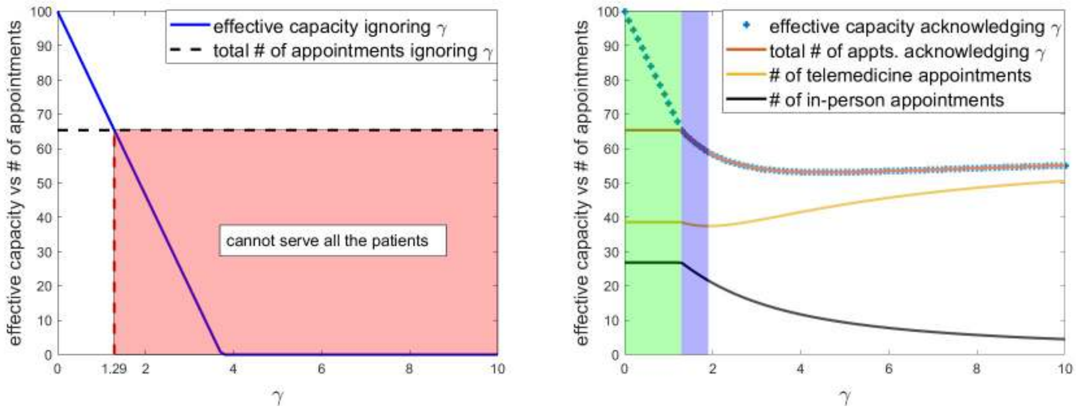
In this section, we offer several extensions and modifications to the optimization model. In Section 3.4.1, a setting is considered where the physicians can contract the virus from the patients, leading to a decrease in effective capacity. In Section 3.4.2, we consider the model with physician sickness from a social planner's perspective by studying a welfare maximization objective. In Section 3.4.3, the perspective is further broadened by including a direct contagion-related cost in the objective. Here, we observe the potential benefit of increasing the contagion awareness of the patients. Finally, in Section 3.4.4, we consider a model where telemedicine appointments may be partially effective, leading to in-person revisits with a certain probability.

3.4.1 Physician Sickness

From March 2020 to April 2020, 39% of doctors had at least one sickness episode, resulting in a 9.1% of sickness absence rate, which is the proportion of doctors unavailable for work due to sick leave (Khorasanee et al. 2021). Exposure to infected patients, work overload, and shortages in personal protective equipment (PPE) are among the main reasons for healthcare workers getting infected during the pandemic (Mhango et al. 2020). Accordingly, we offer an extended model such that the physicians get sick due to the exposure from the patients during in-person appointments. With the physician sickness, the capacity of the healthcare center decreases. The capacity loss due to physician sickness is assumed to be linear in the number of in-person appointments. Then, in the optimization problem (3.1), we update the constraint (3.1j) with

$$m_t C_t + m_i C_i \leq C - \gamma \lambda_i, \tag{3.6}$$

where $\gamma \geq 0$ and γ is a parameter representing the contagion impact of each in-person visit on the physicians. Specifically, a unit increase in the number of in-person appointments eliminates gamma units of physician time due to sickness. The value of γ depends on factors such as the contagiousness and the population-level prevalence



(a) ignoring γ (b) acknowledging γ

Figure 3.6: Total number of appointments and effective capacity when (a) ignoring and (b) acknowledging γ, respectively, under the parameters: $(\lambda, C, V_t, V_i, r, b_0, b_1, b_2, a_t, a_i, m_t, m_i) = (100, 100, 3, 8, 0.1, 0, 1, 1, 1, 1, 1, 1)$, $\gamma \in \{0, 0.1, 0.2, ..., 10\}$.

of the virus, the effective use of PPE, and vaccination among healthcare workers and patients.

Without loss of optimality, we can still set $\lambda_i = C_i$ and $\lambda_t = C_t$ in the optimization problem (3.1) (recall Lemma 1 and see the Appendix A for the proof). Consequently, we update (3.6) with

$$m_t C_t + m_i C_i \leq C - \gamma C_i \quad \Longrightarrow \quad m_t C_t + (m_i + \gamma) C_i \leq C,$$

In the modified constraint, γC_i denotes the capacity loss due to the sick physicians. As the number of in-person appointments increases, more physicians get infected and fall sick, and thus the effective capacity, denoted by $C - \gamma C_i$, decreases. The only difference between constraint (3.1j) and the modified constraint is the change of the parameter m_i to $m_i + \gamma$. Therefore, all the results presented so far continue to hold under this modification.

Let us consider the updated model in which the prices (p_t, p_i) are also decision variables, and the objective is to maximize the revenue. We present a numerical example in Figure 3.6 to show the importance of acknowledging physician absence due to sickness. In Figure 3.6a, the provider ignores the impact of the sick physicians on the effective capacity, allocating the capacity as if $\gamma = 0$ even when $\gamma > 0$. When $\gamma = 0$, the total number of appointments is $65.4 = C_i^*(\gamma = 0) + C_t^*(\gamma = 0)$, and as γ increases, the total number of appointments does not change. However, as γ increases, the effective capacity, which is $C - \gamma C_i$, decreases. When γ equals $1.29 = (C - m_i C_i^*(\gamma = 0) - m_t C_t^*(\gamma = 0))/C_i^*(\gamma = 0)$, the effective capacity is binding. After that point, the effective capacity becomes less than the total number of appointments, and the healthcare center cannot serve all the patients. In Figure 3.6a, the shaded region depicts the γ parameter region where the healthcare center cannot operate successfully. As γ exceeds the threshold $3.73 = C/C_i^*(\gamma = 0)$, the effective capacity becomes zero, i.e., all the physicians are sick.

In Figure 3.6b, the provider acknowledges sick physicians in capacity allocation decisions. Consequently, the total number of appointments never exceeds the effective capacity. There are three different regions represented by different colors. In the first (green) region ($\gamma \in [0, 1.29]$), the effective capacity is not binding, and the number of appointments does not change in γ. In the second (purple) region ($\gamma \in [1.29, 1.9]$), as γ increases, the number of telemedicine appointments decreases. Here, the capacity loss is relatively small, and the revenue derived from in-person appointments outweighs physician well-being (recall Theorem 3, where it is proven that if $r > 0$, the price of an in-person appointment is strictly greater than the price of a telemedicine appointment). In the third (white) region, the in-person appointments consume a significant amount of capacity due to the sick physicians, and thus telemedicine capacity increases in γ. For the regions where the effective capacity is binding, we observe a decrease in the number of in-person appointments as γ increases. The effective capacity does not change much at relatively high values of γ due to the sharp decrease in in-person appointments. As gamma becomes sufficiently large, the in-person channel capacity is so small that we could practically consider this channel as closed. Overall, this example demonstrates that physician sickness changes the optimal capacity allocation between the channels significantly and in a non-monotonic way.

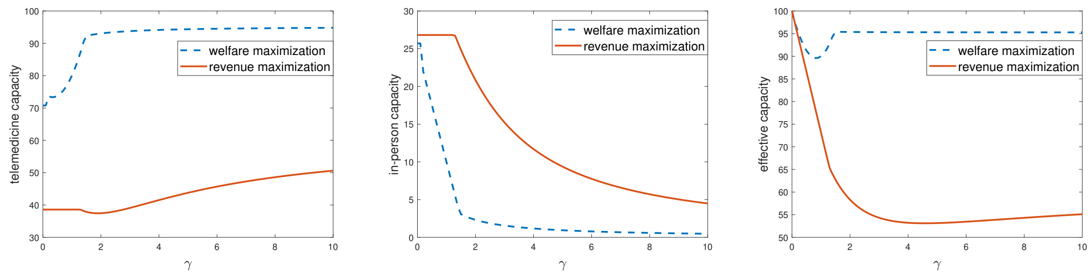
3.4.2 Welfare Maximization

Here, we study the objective of maximizing welfare which is defined as the total net non-monetary utility of the patients. By Lemma 1, the formal welfare definition is as follows.

$$
\begin{aligned}
&a_t p_t C_t + a_i p_i C_i + (1 - a_t) p_t C_t + (1 - a_i) p_i C_i && \text{(3.7a)}\\
&\quad - (1 - a_t) p_t C_t - (1 - a_i) p_i C_i && \text{(3.7b)}\\
&\quad + C_t (V_t - a_t p_t) + C_i (V_i - a_i p_i - r R(C_i)) && \text{(3.7c)}\\
&= C_t V_t + C_i (V_i - r R(C_i)). && \text{(3.7d)}
\end{aligned}
$$

The term in (3.7a) is the revenue of the healthcare provider that is obtained from both the patients and the insurance company. The term in (3.7b) is the payment made by the insurance company to the healthcare provider. The term in (3.7c) is the total net utility of the patients. The welfare is equal to the term in (3.7d), and it does not contain any monetary value because the money stays within the society. Consequently, the welfare is the total net non-monetary utility of the patients. The welfare takes into account the negative effect of contagion on society by the term $-C_i r R(C_i)$. It takes into account the negative effect of the pandemic on physicians indirectly: As the physicians get infected and fall sick, the effective capacity decreases (recall Section 3.4.1), so does the welfare.

In the numerical example presented in Figure 3.7, the dashed and solid lines show the changes in optimal capacities as γ increases under the welfare and the revenue maximization objectives, respectively. In Figure 3.7c, we observe that under the welfare maximization objective, the effective capacity decreases for relatively small values of γ, and it quickly increases and becomes stabilized. For small γ values, the in-person capacity is relatively large, as it has a smaller impact on the effective capacity. Despite the monotonic decrease in the in-person capacity, it does not compensate for the increase in γ, resulting in a decrease in effective capacity $(C - \gamma C_i)$. Under revenue maximization, the decrease and increase in the effective



(a) telemedicine capacity (b) in-person capacity (c) effective capacity

Figure 3.7: Comparisons of the optimal (a) telemedicine, (b) in-person, and (c) effective capacities between the revenue maximization and the welfare maximization objectives as γ increases under the parameters: $(\lambda, C, V_t, V_i, r, b_0, b_1, b_2, a_t, a_i, m_t, m_i) = (100, 100, 3, 8, 0.1, 0, 1, 1, 1, 1, 1, 1), \quad \gamma \in \{0, 0.1, 0.2, ..., 10\}$.

capacity take a longer time compared to welfare maximization due to the higher in-person capacity allocation (Figure 3.7b). Finally, in Figure 3.7a, under welfare maximization, for $\gamma = 0$ and $\gamma = 0.1$, the effective capacity is not binding for the total capacity allocated, and consequently, the values of C_t and C_i do not change. When $\gamma = 0.2$, the effective capacity becomes binding and the capacities of C_t and C_i are optimized at a new point, which can be seen as an instant change in the capacities. Until $\gamma = 1.5$, both C_t and C_i change monotonically in different directions, relatively steeper. After that value, the change in both capacities is tapered off as C_i becomes so small that the change in γ has little impact on the effective capacity, which is reflected in the optimal telemedicine and in-person capacities.

Figure 3.7 shows that the optimal telemedicine, in-person, and effective capacities under the welfare maximization objective are greater, less, and greater than the optimal ones under the revenue maximization objective, respectively. Because the optimal in-person appointment capacity is relatively small under the welfare maximization objective, the number of sick physicians becomes relatively small as well. Therefore, the effective capacity under the welfare maximization objective is greater than that under the revenue maximization objective. We observe that a multichannel health system that is designed according to a welfare objective emphasizes the telemedicine channel over the more traditional in-person channel during peaks of an epidemic and thus protects both patient and healthcare worker well-being. If we were to consider the disutility of sick physicians in the welfare definition, this effect would be even stronger.

3.4.3 Managing Contagion Awareness

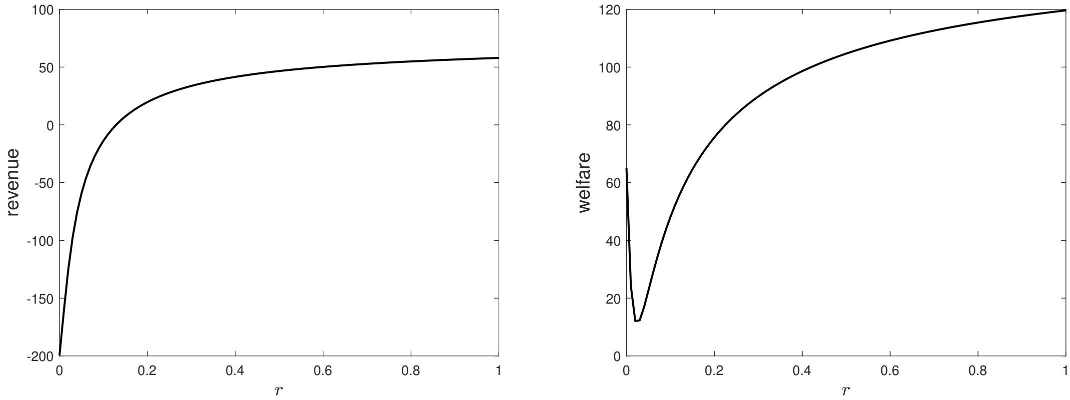
In the previous subsections, we observed that the pandemic affects the revenue-maximizing provider through the channel choices of the patients. When the objective is to maximize welfare, a social planner considers the contagion awareness of the patients through their utilities. Here, we contain a direct cost accounting for patients being infected in the healthcare center and getting sick in the objective. Similar to the explanation of Shumsky et al. (2021) in the retail context, this cost can be related to the damaged reputation for the revenue-maximizing provider, and for the welfare-maximizing social planner, it may include the costs of illness and mortality. Accordingly, in this section, we study a setting where the provider incurs a direct cost due to the infected patients falling ill. We explore how the contagion awareness level of the patients affects the revenue and the welfare.

There is a disease burden due to the infected patients represented by the term $d\phi C_i$ in the objective function. The fraction of in-person patients that are infected in the healthcare center is denoted by $\phi \in [0, 1]$. It is determined by factors such as the contagiousness and the population-level prevalence of the virus and preventive measures in place. The burden of a diseased patient is denoted by d where $d > 0$. By Lemma 1, the new revenue and the welfare definitions are

$$p_t C_t + C_i(p_i - d\phi), \qquad V_t C_t + C_i(V_i - rR(C_i) - d\phi),$$

respectively, and we update the objective function of (3.1) with these new versions, accordingly.

In Figure 3.8, we present the updated revenue and welfare values under various contagion awareness parameters in a numerical experiment where the burden of a



(a) revenue (b) welfare

Figure 3.8: Changes in (a) the revenue and (b) the welfare as contagion awareness, r, increases under the parameter set: $\lambda = 100$, $C = 150$, $\phi = 0.3$, $d = 15$, $\gamma = 0.5$, $m_t = m_i = 1$, $a_t = a_i = 1$, $V_t = 2$, $V_i = 5$, $p_t = 1$, $p_i = 2$, $b_0 = 0$, $b_1 = b_2 = 1$, $r \in \{0, 0.01, 0.02, ..., 1\}$.

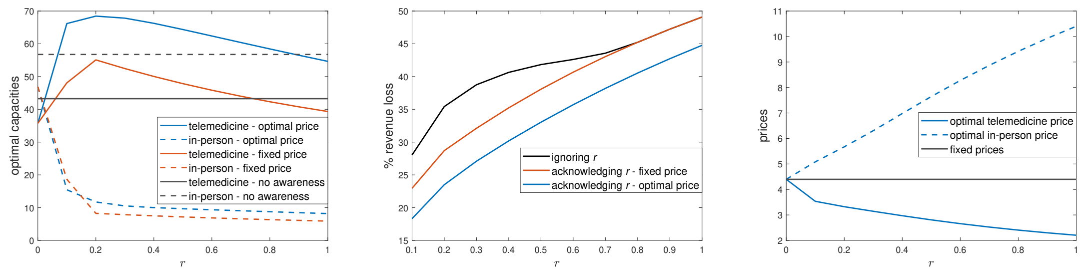
sick patient is quite high. We consider fixed prices to focus on a case where the healthcare provider may not have control over the prices. By setting $\alpha = 1$, we enforce Scenario 1, in which the provider offers both appointment types to all patients. In Figure 3.8a, we see that the revenue increases monotonically as r increases. As the patients become more contagion-aware, the number of telemedicine appointments increases while the number of in-person appointments decreases. Therefore, as r increases, the burden of the infected patients decreases, and the revenue increases. In Figure 3.8b, we see that the welfare has a non-monotonic behavior. Because the net utility of the in-person channel is greater than that of the telemedicine channel (that is, because $V_i - p_i > V_t - p_t$), if r is small, the optimal solution keeps the number of in-person appointments relatively high. As r increases, more patients choose the telemedicine channel, and the burden due to the infected patients decreases. However, when r is small, the decrease in the burden does not compensate for the welfare loss due to the patients switching from in-person to the telemedicine channel. As r exceeds a threshold, welfare increases monotonically.

In conclusion, if the burden of an infected patient is sufficiently large, increasing the contagion awareness level of the patients may increase both the revenue and the welfare. This shows the importance of modulating the contagion awareness level of the patients, which can be done by sharing information with them or by educating them on the contagion risks. In Figure 3.8, the rapid increase in the revenue and the welfare for relatively small values of r shows that a little effort in increasing patient awareness goes a long way in maximizing the revenue and the welfare.

3.4.4 Partial Effectiveness of Telemedicine

In this section, we relax the perfect substitutability assumption of the telemedicine channel. Specifically, a telemedicine appointment can require a follow-up in-person appointment, depending on its virtualization potential (Ayabakan et al. 2024). For mental health and psychiatry, 15% of telemedicine visits result in an in-person follow-up visit (Gerhart et al. 2022). Revisits have certain disadvantages for both patients and the healthcare provider. For patients, a revisit means spending additional time to get treatment. Moreover, in case of a revisit, patients will be exposed to the risk of infection. Lastly, the price of an in-person appointment can be higher than the price of a telemedicine appointment, and in our setting, the in-person appointment price is charged to the revisiting patients. For the healthcare provider, revisits can consume additional capacity. A probability of a revisit results in a decrease in telemedicine's attractiveness, which can result in a demand loss. Despite these disadvantages, under certain conditions, revisits can increase revenue and welfare simultaneously. We will illustrate this in this subsection.

We assume that patients know the revisit probability and they consider it in their channel choices. We also assume that at each booking horizon, the model parameters are the same, and thus, the capacity allocation and pricing problem is stationary in time. We ignore the physician infection and focus solely on the impact of revisits. Let τ denote the revisit probability. Without loss of optimality, we can still set $\lambda_t = C_t$ and $\lambda_i = C_i$ (see Appendix A for the proof and recall Lemma 1). The utilities of the telemedicine and in-person channels in the presence of revisits



(a) capacities (b) revenue loss (c) prices

Figure 3.9: Changes in (a) the optimal capacity allocation, (b) the revenue loss, and (c) the prices in a setting with revisits ($\tau = 0.15$) as the contagion awareness parameter, r, increases under the parameter set: $C = \lambda = 100$, $R(C_i^e) = C_i^e$, $V_t = V_i = 5$, $m_t = m_i = 1$, $a_t = a_i = 1$, $h = 1$, $r \in \{0, 0.1, 0.2, ..., 1\}$ and under the fixed ($p_t = p_i = 4.40$) and optimal prices.

are denoted by (U_t', U_i') such that

$$U_t' := (1-\tau)(V_t - a_t p_t) + \tau(V_i - a_i p_i - rR(C_i^e) - h) + \epsilon_t,$$
$$U_i' := V_i - a_i p_i - rR(C_i^e) + \epsilon_i,$$

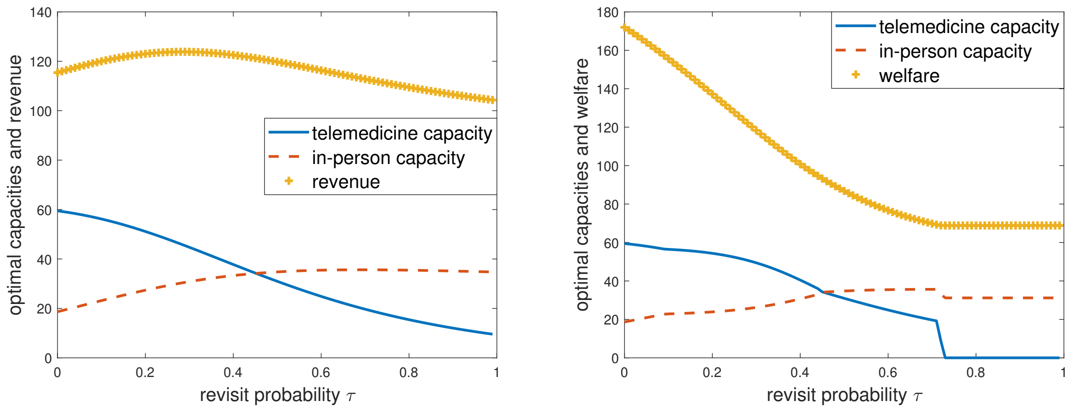
where $C_i^e := C_i + \tau C_t$ denotes the effective capacity for the in-person channel and h is a parameter denoting the disutility for needing an in-person revisit. This disutility includes the hassle of making another appointment, the additional time spent visiting the healthcare center, etc. In the existence of revisits, both telemedicine and in-person channels have negative network effects, creating endogenous patient choices. Because we consider a time-stationary model, the revisiting patients at a particular booking horizon are the telemedicine patients from previous booking horizons.

If a telemedicine appointment results in an in-person revisit, we assume that the provider only charges for the in-person revisit. Consequently, the revenue and the welfare are

$$(1-\tau)p_t C_t + p_i C_i^e,$$
$$C_t((1-\tau)V_t - \tau h) + C_i^e \left(V_i - rR(C_i^e)\right),$$

respectively. We solve the optimization problem (3.1) under the updated channel utilities. Figure 3.9 is the version of Figure 3.5 under a revisit probability $\tau = 0.15$ and a disutility cost of a revisit $h = 1$. In Figure 3.9, the fixed prices denote the optimal telemedicine and in-person appointment prices when $r = 0$, and they are equal to each other. In Figure 3.9a, when $r = 0$, the telemedicine capacity is smaller than the in-person capacity because of the disutility of a revisit after a telemedicine appointment. When $r = 0$, the in-person channel is more attractive as it does not have the revisit risk, and there is no contagion effect. For sufficiently small values of r, the impact of contagion decreases the utility of the in-person channel, and that results in an increase in the telemedicine capacity. Different from Figure 3.5a, in Figure 3.9a, when r is sufficiently large, the optimal telemedicine capacities under both the fixed and the optimal prices decrease. This is because as the contagion awareness increases, the utility of choosing the telemedicine channel decreases, which, in turn, decreases the demand for the telemedicine channel. In Figure 3.9b, we see that when $\tau > 0$, acknowledging the contagion effect helps to mitigate the revenue loss, similar to Figure 3.5b (where $\tau = 0$) for relatively small values of r. For sufficiently large values of r, because there are negative network effects in both the telemedicine and the in-person channels, the demands for both channels decrease significantly, and the capacity becomes abundant. Consequently, the benefit of acknowledging r in capacity allocation decisions decreases. We see that optimizing the prices has value in mitigating the revenue loss, independent of r. Figure 3.9c shows that as r increases, the optimal in-person price increases and the optimal telemedicine price decreases (recall Theorem 3). Although both channels have negative network effects, this effect is smaller for the tele-channel as only a portion of telemedicine appointments have a disutility of contagion. As a result, the change in the in-person price in r is greater than the change in the telemedicine price in r.

So far, we see that the revisits are not desired by the healthcare provider due to the negative network effect that they create in the telemedicine channel. However, in Figure 3.10a, we present a numerical experiment showing that revisits can increase

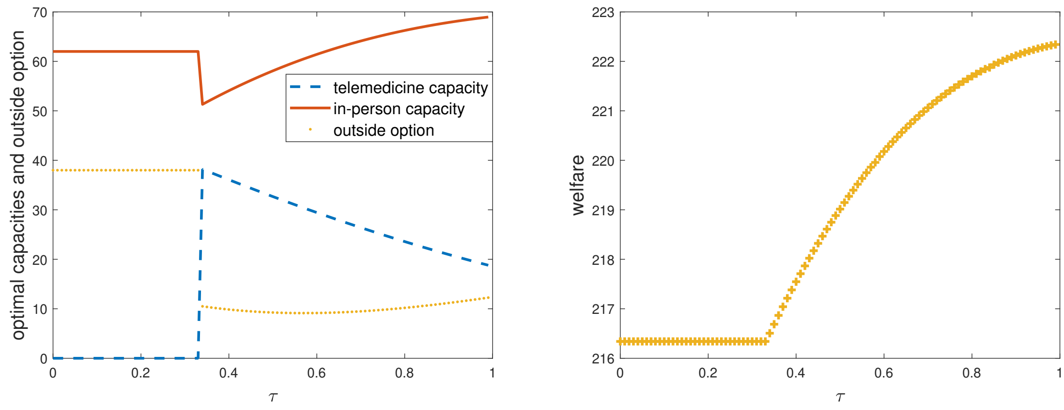


(a) capacities and revenue (b) capacities and welfare

Figure 3.10: Changes in (a) the optimal capacities and revenue and (b) the optimal capacities and welfare as the revisit probability, τ, increases under the parameters: $C = \lambda = 100$, $V_t = 2$, $V_i = 5$, $p_t = 1$, $p_i = 3$, $m_t = m_i = 1$, $a_t = a_i = 1$, $R(C_i^e) = (C_i^e)^{b_2}$, $b_2 = 0.5$, $r = 0.5$, $h = 1$, $\tau \in \{0, 0.01, 0.02, ..., 0.99\}$.

revenue. In Figure 3.10a, we present the optimal revenue under fixed prices and various revisit probabilities. Because the in-person appointment price is higher than the telemedicine appointment price, the revisits enable the revenue maximizer to charge the telemedicine patients the high in-person price. The revisits provide additional revenue while not decreasing the demand for the in-person channel significantly due to the relatively weak contagion effect in this numerical example. Consequently, the healthcare provider can obtain a higher revenue under a strictly positive revisit probability. Different from the case of revenue maximization, Figure 3.10b shows that welfare decreases as the revisit probability increases, and the telemedicine channel is not offered when the revisit probability exceeds a certain threshold. Here, the tele-channel becomes less desirable due to a high revisit probability resulting in an increased contagion effect.

Figure 3.10b is intuitive, as the social planner should desire a fully effective telemedicine channel. However, Figure 3.11 shows that this may not be the case all the time. In Figure 3.11a, when the revisit probability is small, only the in-person



(a) capacities and outside option (b) welfare

Figure 3.11: Changes under welfare maximization in (a) the optimal capacities and the number of outside options selected and (b) the welfare as the revisit probability, τ, increases under the parameters: $\lambda = C = 100$, $R(C_i^e) = (C_i^e)^{b_2}$, $V_i = 3.75$, $V_t = 2$, $p_i = 3$, $p_t = 1$, $b_2 = 0.01$, $r = 0.25$, $h = 1$, $\tau \in \{0, 0.01, 0.02, ..., 0.99\}$.

channel is offered to the patients. When the revisit probability is sufficiently large, the social planner offers the telemedicine channel, and the welfare starts to increase in the revisit probability. The reason for this result is as follows. Observe that the valuation of the in-person appointments is larger than the one of the telemedicine appointments ($V_i = 3.75 > V_t = 2$) and the contagion effect is sufficiently small ($r = 0.25$, $b_2 = 0.01$) in the numerical experiment depicted in Figure 3.11. Therefore, a patient making an in-person appointment obtains a higher net utility than a patient making a telemedicine appointment. When the revisit probability is small, the tele-channel is not offered because the social planner does not want to reduce the demand for the in-person channel. When the revisit probability is large, the tele-channel is offered because of the revisits: a revisiting telemedicine patient obtains a higher net utility than a telemedicine patient who does not make a revisit. Consequently, the welfare increases in the revisit probability as shown in Figure 3.11b. A similar pattern is observed under the revenue maximization objective (not shown for brevity). However, the revenue maximizer opens the telemedicine channel at a higher threshold of the revisit probability compared to the welfare maximizer. This example underlines the complexity of the relationship between the revisit probability and the contagion effect.

3.5 Concluding Remarks for Chapter 3

During the recent COVID-19 pandemic, the fear of contagion among patients resulted in a significant decrease in patient demand. The telemedicine channel experienced unprecedented growth during this period. Nevertheless, its uptake was not sufficient to overcome the delay in needed care by a large portion of the population.

Healthcare systems endured significant revenue losses. In this chapter, we focus on a multichannel healthcare delivery system that can jointly offer telemedicine and in-person channels. We show the impact of an epidemic in this multichannel system where patient channel choice is driven by the contagion awareness of patients. The model we formulate demonstrates the importance of acknowledging patient fear in operational decisions. Our results characterizing the revenue-maximizing capacity ratio and the price gap between the channels as a function of patient contagion awareness, demonstrate how, during epidemic peaks, healthcare providers can mitigate a significant portion of revenue losses by shifting existing capacity to the telemedicine channel or providing discounts (or other forms of incentive) for care through this channel.

The importance of the telemedicine channel in providing healthcare access during epidemics is even higher when we embed the physician sickness due to getting infected by patients (affecting the capacity of the provider) or the burden of the sick patients (affecting the revenue of the provider) in our model. When we analyze the model from a social planner's perspective, we observe that the consideration of the well-being of the patients in the planner's objective also protects the physicians. Our results highlight the importance of the existence of a social planner for the sustainability of healthcare systems that suffer from insufficient capacity due to infected physicians during epidemics. When we further acknowledge the burden of sick patients in the model, we demonstrate that higher patient awareness can create value for healthcare systems by attracting more patients to the telemedicine channel. The relationship between awareness and value is mostly concave, implying that some awareness captures a big portion of the revenue or welfare to be gained. This suggests that healthcare providers can benefit from practices that improve patient awareness of infection risk in the in-person channel, which is studied in the next chapter.

The telemedicine channel may not always be a perfect substitute for the in-person channel, resulting in in-person revisits. When we extend our model to account for revisits, we observe that contagion-aware choice creates additional interactions between the two channels, which are hard to foresee. Under a sufficiently small revisit probability, we observe that the importance of acknowledging the contagion awareness of patients in capacity allocation and pricing decisions is preserved. Consequently, the telemedicine channel is still valuable even if it is not fully effective. We illustrate that different policies can be preferred by the provider and the social planner. While the former can offer the telemedicine channel for a medical condition with a high revisit probability to increase revenue, the latter can decide not to offer the telemedicine channel to maximize welfare.

The findings of Chapter 3 motivate the subsequent chapter, which focuses on patient demand management during epidemics (or respiratory virus seasons) by offering effective interventions to increase patient choice for the telemedicine channel.

Chapter 4

INTERVENTIONS TO MANAGE PATIENT CHANNEL CHOICE

In this chapter, we study the impact of informational interventions (nudge messages) on the healthcare channel decisions of patients during times of infectious diseases. The messages that we study focus on two dimensions of the appointment channels: infection risk and appointment wait time. In addition to the informational interventions, we consider direct drivers of patient channel choice. We focus on two key drivers: pricing (price difference) and capacity management (appointment wait time difference). The impact of informational interventions in managing patient demand is important, as, from the healthcare provider's point of view, pricing and capacity decisions may be costlier to apply.

4.1 Theory and Hypotheses

The infection risk associated with the in-person channel is one of the determinants of the patient channel choice. Fear of infection is associated with a decrease in hospital visits during the COVID-19 pandemic (Lazzerini et al. 2020b, Wong et al. 2020). This supports the role of infection risk consideration in patient choice. The infection risk includes a risk of getting infected (self-risk) as well as a risk of infecting others. The latter is associated with the prosociality concept. Prosocial individuals are more likely to follow social distancing rules, stay home when sick, and purchase face masks (Campos-Mercade et al. 2021). There is a positive relationship between prosocial behavior and people's COVID-19 vaccination intentions (Yu et al. 2022). One can mitigate both self-risk and the risk of infecting others by making an online appointment instead of a face-to-face one.

Underlining self-risk versus the risk for others with informational messages is shown to have different impacts on people's conformance to the rules and regulations set by the governments during the COVID-19 pandemic. There are mixed results in the literature. Hume et al. (2021) and Pfattheicher et al. (2020) show that referring to a specific person who is affected by the pandemic and making people question the ethical dimension of social distancing behavior is useful in increasing compliance. Similarly, the nudge message emphasizing protecting people around from the virus is more effective in maintaining a social distance than the emphasis on protecting the individual himself (Banker et al. 2022). Contrary to these findings, Neumer et al. (2022) suggest that targeting oneself rather than fellow citizens is more effective in increasing compliance with the social distancing rules. Finally, Favero and Pedersen (2020) find that emphasizing the effects of individuals' choices on society, such as attending crowded events during the pandemic and not using a mask, does not affect compliance with social distancing rules.

The framing of the informational messages (gain/positive vs loss/negative) can influence their effectiveness in changing behavior (Nan et al. 2018). There is no clear consensus in the literature in terms of framing effects. A negative frame indicating risks associated with not complying with a doctor's advice is more effective than a positive frame indicating benefits of complying (Peng et al. 2013). A loss-framed message is more effective than a gain-framed one in increasing social distancing behavior, which is mediated by an increase in perceived risk and worry (Neumer et al. 2022). To increase risk perception, a loss-framed message is more effective, while to motivate self-care behaviors, a gain-framed message is more effective (Gantiva et al. 2021). Gain-framed messages are more effective in promoting preventive behavior (such as using sunscreen), and loss-framed messages are more effective in promoting detective behavior (such as screening for mammography) (Rothman et al. 2006). Gain-framed messages are more effective than loss-framed messages in promoting prevention behaviors (Gallagher and Updegraff 2012), and health messages intended to encourage COVID-19 preventive behaviors should be framed in terms of gains rather than losses (Soofi et al. 2020). A gain-framed altruistic message emphasizing protecting the lives of others is found to be an effective nudge in reducing people's frequency of going out and contacting others (Sasaki et al. 2021). Contrary to these findings, Sanders et al. (2021) and Bahety et al. (2021) state that sharing information focused on gain or loss does not affect compliance with public health rules.

In summary, the literature on the impact of emphasizing self versus others' risk and the impact of negative versus positive framing in inducing a certain behavior has mixed results. To the best of our knowledge, there is no study on the impact of an informational intervention, an infection message, on the health channel choice of patients. Additionally, we consider the implications of how we frame the message. On the one hand, focusing on increasing the risk perception of patients, a negatively framed information message that underlines the infection risk of the face-to-face channel can increase the percentage of online appointments chosen. On the other hand, focusing on the infection-prevention perspective of online appointments, a positive framing can be effective in increasing the percentage of online appointments chosen. In addition to the framing, including the risk for others in the message can induce prosocial behavior and be effective. However, focusing only on self-risk can increase attention by making the message more direct. These arguments lead to the following hypotheses.

Hypothesis 1a *The infection message emphasizing the self-risk and the risk for others associated with making a face-to-face appointment (negative framing and prosociality) increases the likelihood of patients choosing the online appointment channel compared to not showing a message.*

Hypothesis 1b *The infection message emphasizing the elimination of self-risk by making an online appointment (positive framing) increases the likelihood of patients choosing the online appointment channel compared to not showing a message.*

Hypothesis 1c *The infection message emphasizing the elimination of self-risk and the risk for others by making an online appointment (positive framing and prosociality) increases the likelihood of patients choosing the online appointment channel compared to not showing a message.*

Pricing is frequently used in the healthcare literature to encourage healthy consumption. Public health interventions to promote healthy consumption include tobacco taxes, alcohol taxes, and healthy food subsidies (Nghiem et al. 2013). A 10% increase in cigarette prices reduces cigarette consumption by 5% to 7% (Gallus et al. 2006). A price increase is more effective in improving the nutritional quality of diets than a price reduction (Cornelsen et al. 2019). A 20% increase in the price of sugar-sweetened drinks is estimated to reduce obesity prevalence in the UK by 1.3% (around 180,000 people) (Briggs et al. 2013). In terms of appointment choices of the patients, cost-related risk factors (time cost, transportation cost, etc.) increase the likelihood of patients making an online appointment (Ye and Wu 2022). Patients prefer lower amounts of out-of-pocket payments when scheduling appointments (Liu et al. 2018, Snoswell et al. 2020). Patients with high out-of-pocket costs for in-person visits are more likely to choose a telemedicine visit (Reed et al. 2020). 23.5% of patients switched from an in-person visit to a video visit when in-person visits cost 20$ more than telemedicine visits (30$ vs 10$), while 61.7% of patients switched to in-person visits when video visits have 20$ higher costs than in-person visits (Predmore et al. 2021), indicating different price elasticities for the channels. To see the effectiveness of the infection message on telemedicine adoption relative to a direct control, we include a price difference intervention between the in-person and telemedicine channels. We use a 25% price increase due to (Mytton et al. 2012) that suggests at least a 20% price difference to have a significant effect on behavior change. That leads to the following hypothesis.

Hypothesis 2 *Setting a 25% higher price for a face-to-face appointment increases the likelihood of patients choosing the online appointment channel compared to an equal price.*

In addition to infection risk and price, there are others factors that affect a patient's channel choice. While more accurate diagnosis and treatment drive an in-person visit, eliminating the spread of infectious diseases, decreasing cost and waiting time, and removing distance barriers drive a telemedicine visit (Moulaei et al. 2023). Telemedicine can reduce indirect patient costs such as time and money spent during travel, missed work, and time spent in the waiting room (Imlach et al. 2020). Familiarity with the practitioner (46%) and waiting time until the next available appointment (22%) are more important in appointment preferences of the patients than the consultation mode being video versus in-person (18%), waiting time on the appointment day (13%), and opening hours (1%) (von Weinrich et al. 2022). Time until the appointment is the most important factor that is considered by the patients, followed by the severity of the problem, relationship with the primary care provider, the flexibility of reception hours, waiting time before consultation, infection risk, arrival time, and patient type (Mozes et al. 2022). Focusing on one of the most important drivers, we explore the impact of the appointment wait time difference between the channels on the patient channel choice. We choose to study the appointment wait time as it affects the patient choice significantly, and it is a result of the healthcare provider's capacity/resource management policy that can be easily observed by the patient prior to making an appointment.

After choosing the appointment wait time as a dimension to study, we want to find the most effective way to nudge the telemedicine channel's appointment wait time advantage to increase its adoption. Liu and KC (2023) study a nudge message where patients are reminded of the long wait time until the next available appointment in case the current appointment is missed. They find that the reminder message reduces the no-show rates. In their setting, the nudge message signals the quality of the provider by stating that the provider has a long list of patients in the queue and, thereby, missing an appointment results in a long wait. Long waits can lead to worsening health outcomes for the patients (Prentice and Pizer 2007, Reichert and Jacobs 2018). We study an appointment wait time message that emphasizes the shorter wait time advantage of the online channel in terms of preventing deterioration of the health condition by allowing patients to see the doctor sooner. Consistent with the literature that shows the effectiveness of the positive framing on the messages regarding preventive behavior (Gantiva et al. 2021, Rothman et al. 2006, Gallagher and Updegraff 2012, Soofi et al. 2020), we use a positive framing by highlighting the online channel's role in preventing health condition deterioration through allowing more timely access to care. That leads to the following hypothesis.

Hypothesis 3 *The appointment wait time message emphasizing the wait time advantage of online appointments and thereby, the prevention of health condition deterioration (positive framing), increases the likelihood of patients choosing the online appointment channel compared to not showing a message.*

Telemedicine appointments can allow doctors to allocate less time to each patient, which increases the capacity to see more patients (Haleem et al. 2021). The inadequate on-site doctor capacity can be addressed with telemedicine by hiring flexible off-site doctors who can offer services beyond work hours (Sun et al. 2020). The capacity implications of telemedicine can result in a decrease in appointment wait times, which we refer to as the systems perspective. Hypothesis 3 adopts this approach where the provider offers different appointment wait times for the channels, which is further emphasized with a nudge message. However, even when the provider offers similar wait times for the channels, there can still be a wait time difference. Graetz et al. (2022) study a setting where in-person and telemedicine appointments have similar scheduling availability. They find that with telemedicine, patients can see a doctor more quickly, as a tele-appointment allows patients to access healthcare without the need to arrange transportation. Related to travel burdens, convenience is a major determinant in the patient's choice to use telemedicine (Eldaly et al. 2022), and it considers not having to miss school or work (Bator et al. 2015, Evers et al. 2022) and the comfort of being at home (Vinella-Brusher et al. 2022). Eliminating the need to travel to a hospital, a telemedicine appointment takes a shorter time to complete, which can allow it to fit into a patient's schedule sooner than a face-to-face appointment. Even in settings where the healthcare provider can ensure similar appointment wait times for the channels, there is a potential appointment wait time difference from the patient's perspective due to convenience. We want to test the effectiveness of a positively framed informational message that emphasizes telemedicine's ease of scheduling (fitting into the schedule of patients), leading to a sooner appointment. We use positive framing, as seeing the doctor sooner rather than later prevents the risk of the health condition deterioration. That leads to the following hypothesis.

Hypothesis 4 *The convenience message emphasizing the ease of online appointments in terms of fitting into the schedule and leading to seeing the doctor sooner (positive framing) increases the likelihood of patients choosing the online appointment channel compared to not showing a message.*

Hypotheses 3 and 4 focus on the appointment wait time difference between the channels. This provides an alternative mechanism for healthcare providers who do not want to use patients' infection fear to manage patient demand.

Infection risk perception is an important factor that drives compliance with measures to control COVID-19 (Wise et al. 2020, Siegrist et al. 2021). A low level of risk perception is one of the reasons why people do not adhere to the COVID-19 prevention and control guidelines (Young and Goldstein 2021), while high levels of risk perception towards COVID-19 predict compliance with preventive behaviors and social distancing measures (Cipolletta et al. 2022). Accordingly, people with a high infection risk perception would try to avoid risks of infection whenever possible. Focusing on the infection risk prevention role of the online channel, one would expect a positive relationship between infection risk perception and telemedicine adoption. We control for this effect in our analysis.

Beyond the individual impacts of an infection message and infection risk perception of the patients on channel choice, we are interested in the potential moderating effects of risk perception on the effectiveness of the infection message. The literature about the nudge effectiveness on people with prior beliefs and attitudes has contradictory results. In terms of spending behavior, an opportunity cost reminder nudge is found to be more effective on people who already spend too little compared to people who actually need to reduce spending (Thunström et al. 2018). In terms of eating habits, consumers with lower self-control place less value on the calorie salience nudge, reducing its effectiveness (Thunström 2019). People with higher environmental attitudes accept green products promoted with a default nudge more compared to people with lower pro-environmental preferences (Taube and Vetter 2019). In our context, these results would indicate that the infection message is more effective in increasing the adoption of telemedicine in patients with higher infection risk perception levels. In contrast, Bonander et al. (2023) show that a vaccination nudge is more effective in younger individuals with lower perceived risks toward COVID-19. Similarly, Barari et al. (2020) and Sasaki et al. (2021) find that nudges are less effective on people with already high compliance levels, related to the term "ceiling effect", arguing that there is no room for further improvement. These findings reflect that an infection message is more effective in increasing the adoption of telemedicine in patients with lower infection risk perception levels. Finally, de Ridder et al. (2022) argue that nudges are more effective in individuals with less developed preferences. In other words, people with strong preferences against or in line with a nudge are less affected by it. The mixed findings in the literature result in two countervailing hypotheses.

Hypothesis 5a *The infection message is more effective among patients with higher infection risk perceptions in encouraging patients to choose the online appointment channel.*

Hypothesis 5b *The infection message is more effective among patients with lower infection risk perceptions in encouraging patients to choose the online appointment channel.*

Travel costs and a lack of a driver or car are among the major transportation barriers for patients (Cochran et al. 2022). The perceived cost of a hospital visit is positively correlated with travel distance, expenditures, and missed work (Bator et al. 2015). Patients and caregivers consider the transportation-related efforts and infection risk to be major concerns of the in-person channel (Mariani et al. 2023). Similarly, patients consider travel time and cost savings to be one of the benefits of telemedicine (Vinella-Brusher et al. 2022). Patients with a longer driving time to a hospital are significantly more likely to choose telemedicine over the in-person channel (Reed et al. 2020). During COVID-19, the likelihood of using telemedicine is 40% more for patients with transportation challenges (Kim et al. 2024). In summary, the literature shows a positive relationship between telemedicine adoption and patients' travel burdens in reaching healthcare facilities. We control for this effect. The travel burden is highly associated with the convenience dimension of telemedicine, yet it is not the only factor. Additional factors related to the convenience of telemedicine appointments include not having to miss work or experience the discomfort of leaving home. The convenience message emphasizes that an online appointment may consume less time than a face-to-face appointment to fit into the schedule of patients, allowing more timely access. The message does not focus on a certain aspect of convenience. As travel burden is shown to be a major consideration by the patients, we want to see whether travel time moderates the effectiveness of the convenience message in increasing the adoption of telemedicine. On the one hand, patients who are located further away from the hospital can be impacted more by the convenience nudge, as it aligns with their attitudes toward making an online appointment (Thunström et al. 2018, Thunström 2019, Taube and Vetter 2019). On the other hand, for patients living closer to the hospital, the travel burden is less significant. These patients may be indifferent between the two channels rather than having a strong preference for the online channel. Bonander et al. (2023) and Venema et al. (2020) show that the nudge messages are more effective in people who are indifferent between the options. In our context, this would imply that the convenience message is more effective in patients with lower travel time to the hospital. In light of these, we have the following countervailing hypotheses.

Hypothesis 6a *The convenience message is more effective among patients with a higher travel time to the hospital in encouraging patients to choose the online appointment channel.*

Hypothesis 6b *The convenience message is more effective among patients with a lower travel time to the hospital in encouraging patients to choose the online appointment channel.*

4.2 Laboratory Experiments

We test the hypotheses developed in the previous section in four controlled experiments. In Studies 1,2, and 3, there is an epidemic scenario of a respiratory virus infection. In Study 4, there is information on respiratory virus seasons. In each study, there is a health condition scenario for which the participants seek treatment. The participants are presented with two channel options, face-to-face and online, and their trade-offs. Specifically, a patient definitely gets treated in a face-to-face appointment, yet she can get infected with a 5% chance. This percentage is determined according to Barranco et al. (2021), which reports studies from the literature with a percentage of hospital-acquired SARS-CoV-2 infections changing between 0-16%. There is no risk of infection in an online appointment, yet there is a 30% chance of not getting treated. In that case, the patient must attend a subsequent face-to-face appointment. The percentage of in-person follow-ups is chosen in the range of numbers reported for different conditions by Gerhart et al. (2022). Considering these trade-offs, participants make their channel choices. Next, they complete several scales from the literature and demographic questions. At the end of the study, they learn about the outcome of their channel choice (see Table 4.2 for a list of outcomes). In the first three studies, participants (undergraduate students) had two incentives to participate in the studies. First, everyone who completed the study obtained additional course credit. Second, those who gave correct answers to both comprehension check questions (see Appendix H) received a bonus in the form of either a lunch ticket or a gift card, depending on the study. In the last study, participants from Prolific were incentivized with monetary payments. Participants who gave a correct answer to the comprehension check question (see Appendix H) gained a bonus payment. Instead of a performance-based incentive, such as assigning each outcome a payoff and providing the gift cards based on the payoffs, we preferred a comprehension-based incentive. There are several reasons for this design choice. First, it is hard to set a pre-defined payoff for all outcomes, as a participant may value getting treatment sooner (without a revisit) but get infected more than getting treated later without an infection, or vice versa. Second, if each outcome is given a payoff, the experiment can be seen as purely an expected payoff maximization, which is not our aim. We wanted to elicit the real channel choices of participants, and consequently, we wanted them to read the information carefully.

In Study 1, we test Hypotheses 1a, 2, 5a, and 5b. There is a negatively framed infection message emphasizing the infection risk associated with making a face-to-face appointment for oneself and others. As an additional benchmark, we study a direct control in the form of a price difference between the channels. In the price difference intervention, there is a 25% price difference in favor of the tele-channel in the scenario. Designing the price intervention as a separate treatment allows us to see the impact of the infection message separate from the price intervention. Finally, we have an interaction group that observes both the price difference and the infection message. In Studies 2, 3, and 4, we focus on one of the most important operational drivers for telemedicine choice, the appointment wait time (von Weinrich et al. 2022, Mozes et al. 2022), keeping the prices equal. In Study 2, we test Hypotheses 1b, 3, 5a, and 5b. The healthcare provider offers a shorter appointment wait time for the online channel, which is embedded in the scenario for all treatments. The appointment wait time is an outcome of the provider's capacity management policy, which is observed by the patients. In this setting, we test the effectiveness of two informational interventions: a positively framed infection message emphasizing the online channel's infection risk prevention role for self and a positively framed appointment wait time message emphasizing the online channel's ability to offer a sooner appointment and thereby preventing health condition deterioration. In Study 3, we test Hypotheses 1c, 4, 5a, 5b, 6a, and 6b. The provider offers the same appointment wait time for the channels. The elimination of transportation-related time and effort makes the tele-channel a convenient mode of healthcare delivery, leading to easier scheduling for the patients. This results in patients being able to make an earlier appointment in the online channel. We test the effectiveness of two informational interventions. First, we test a positively framed infection message that emphasizes the online channel's infection risk elimination role for self and others. Second, we test a positively framed convenience message that emphasizes the ease of fitting an online appointment into a patient's schedule, which allows more timely access. Finally, in Study 4, we test the same hypotheses as in Study 3 on a different participant pool and under information of respiratory virus seasons instead of an epidemic scenario.

In each study, we control for the infection risk perception of the participants. We use the COVID-19 risk perception scale by Plohl and Musil (2021) (see Appendix G.1) as a proxy for the infection risk perception of the patients. Additionally, we test whether participants' infection risk perceptions moderate the effectiveness of the infection message in increasing online channel adoption (Hypotheses 5a and 5b). In Study 1, we use the prosocial behaviors intention scale which is taken from Baumsteiger and Siegel (2019) (see Appendix G.2). Finally, participants' inherent attitudes toward the channels can influence their appointment channel choices. In all four studies, the attitude scales towards receiving online and face-to-face counseling (Rochlen et al. 2004) are used as a proxy to identify and control for personal preferences regarding the medium of online and face-to-face appointment channels (see Appendix G.3).

In all studies, the outcome variable of interest is the channel choice, which is a binary variable (online/telemedicine or face-to-face/in-person). We use logistic regression models to analyze the choices of the participants.

4.2.1 Experiment 1: Pricing vs Infection Risk Messaging

In Study 1, we consider a negatively framed informational message that emphasizes the infection risk associated with making a face-to-face appointment for oneself and others. We also study an instance of a price difference between the channels where a face-to-face appointment is 25% more expensive than an online appointment, which is presented as a part of the scenario.

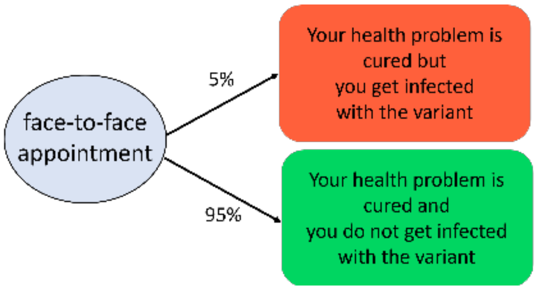
Participants, Design, and Experimental Groups

Study 1 was conducted on 11-24 December 2023. Of 332 participants with complete entries, 32 participants had incorrect answers for both comprehension check questions. As part of our exclusion criterion, their data is removed. The final sample size is 300.

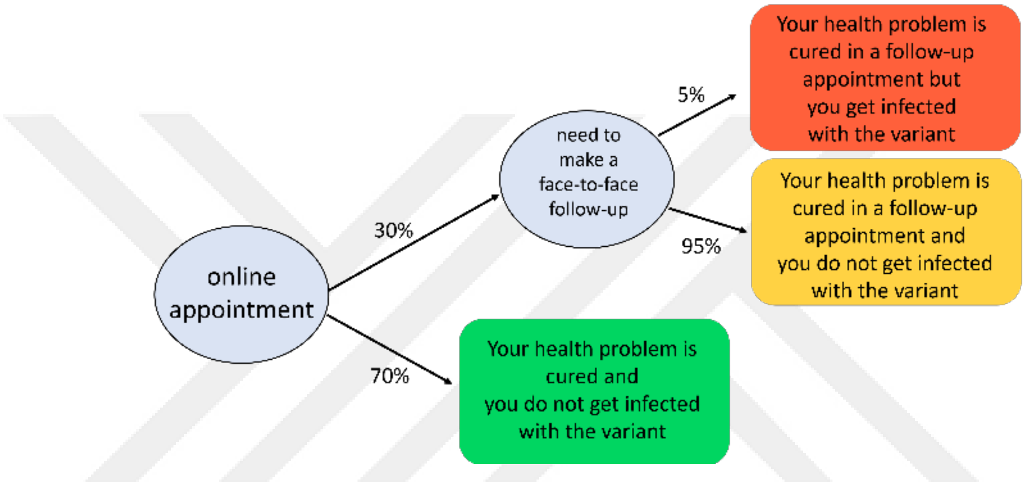
Study 1 is designed as a 2x2 factorial in which participants are randomly assigned to one of the four groups: control (C1), higher price (HP), infection message (IM1), and interaction (HP $\times$ IM1). In groups C1 and IM1, the price of a face-to-face appointment is equal to the price of an online appointment. In groups HP and HP $\times$ IM1, the price of a face-to-face appointment is 25% higher than the price of an online appointment. For the groups IM1 and HP $\times$ IM1, a negatively framed infection message is shared emphasizing the infection risk in the face-to-face channel; "If you have a face-to-face appointment, there is a risk of getting infected by the new variant. If you are infected, you can spread the virus to others, including family members and friends." The nudge message underlines two risks: one for oneself and one for family members and friends. Table 4.1 summarizes the differences among the experimental groups.

In all groups, participants started the experiment after giving their consent to participate. They are presented with a scenario announcing the existence of a new variant of COVID-19. This variant is stated to be spreading fast, affecting people of all ages, and there are no effective vaccines. During the study period, the JN.1 variant of COVID-19 was the most widely circulating variant (Katella 2024, Romo 2024), supporting the validity of our manipulation. According to the scenario, the participants have a health problem unrelated to COVID-19, which is believed to be non-urgent. They are asked to choose between two appointment options: face-to-face and online. The same doctor provides both options, both appointments are readily available, and they have the same appointment duration. There is a 5% infection risk for the face-to-face channel and a 30% revisit risk for the online channel. These trade-offs are illustrated in the experiment with Figure 4.1.

After reading the scenario and learning the trade-offs of the channels, IM1 and HP $\times$ IM1 groups read the infection message. Next, the participants in all groups are asked to make their appointment channel decision between the two options. The participants are assigned to the outcomes randomly with respect to the probabilities



(a) Face-to-face channel



(b) Online channel

Figure 4.1: Trade-offs for the two channels in Study 1

presented in Table 4.2. After the channel choice is made, participants complete four scales: prosociality, COVID-19 risk perception, and attitudes toward online and face-to-face counseling. Following the scales, information on previous online experience, age, and gender is collected. In the last screen, the participants learn the outcome of their appointment choice and whether they are eligible for a lunch ticket.

Summary Statistics

Distribution of the participants to the groups and their appointment choices are provided in Table 4.3. The ratio of participants who choose the online appointment option in the group IM1 is the highest one among the four groups with 54.05%. It is followed by the group HP $\times$ IM1 (50.00%), the group HP (41.67%), and finally the

Table 4.1: The differences of the experimental groups in Study 1

Group	Price	Message
Control (C1)	Equal price	No message
Higher Price (HP)	Face-to-face option has 25% higher price	No message
Infection Message (IM1)	Equal price	Message about infection risk
Interaction (HP $\times$ IM1)	Face-to-face option has 25% higher price	Message about infection risk

Table 4.2: Appointment decisions, probabilities, and outcomes

Decision	Probability	Outcome
Face-to-face	0.05	treated but get infected
Face-to-face	0.95	treated and do not get infected
Online	0.015	treated in the follow-up appointment but get infected
Online	0.285	treated in the follow-up appointment and do not get infected
Online	0.70	treated in the online appointment and do not get infected

group C1 (34.15%). The Pearson Chi-square test is applied to indicate whether the differences between the three intervention groups and the control group are significant. The group IM1 (p-value=0.012) and the group HP $\times$ IM1 (p-value=0.046) are significantly different than group C1 in the percentage of online appointments chosen. The HP group is not significantly different from the group C1 (p-value=0.337).

Recall that in our analyses, we include the participants who gave a correct answer to at least one comprehension check ($N = 300$). For robustness, we repeat the analyses by considering the participants who gave a correct answer to both comprehension checks ($N = 193$). The IM1 group has a partially significant chi-square test result (p-value=0.056). The significance of the HP $\times$ IM1 group is not robust.

Table 4.4 presents the averages and standard deviations of the four scales (PROS, RISK, OCAS, FCAS) and age by group, as well as the percentage of females and the

Table 4.3: Groups and appointment channel choices in Study 1

Group	Face-to-face	Online	Total#	Online%
Control (C1)	54	28	82	34.15%
Higher Price (HP)	42	30	72	41.67%
Infection Message (IM1)	34	40	74	54.05%
Interaction (HP × IM1)	36	36	72	50.00%
Grand Total	166	134	300	44.67%

percentage of participants with previous online experiences. The Cronbach's alpha values for the scales are also reported. Each scale can take any value between 1 and 7. We treat average scale scores as continuous variables and conduct a one-way ANOVA. The results show no significant difference among the four experimental groups (see Appendix J.1).

Model Specification and Results

The dependent variable O_i is a binary variable taking the value of 1 if individual i chooses the online channel and 0 if individual i chooses the face-to-face channel. Consequently, $\mathbf{P}(O_i = 1)$ denotes the probability of individual i choosing the online channel and $\mathbf{P}(O_i = 0)$ denotes the probability of individual i choosing the face-to-face channel. The logistic regression model used in Study 1 is as follows.

$$\log\left(\frac{\mathbf{P}(O_i = 1)}{\mathbf{P}(O_i = 0)}\right) = \beta_0 + \beta_1 HP_i + \beta_2 IM1_i + \beta_3(HP_i \times IM1_i) + \beta_4 RISK_i \\ + \beta_5(RISK_i \times IM1_i) + \beta_6 PROS_i + \beta_7 OCAS_i + \beta_8 FCAS_i + \beta_9 X_i \qquad (4.1)$$

$HP_i = 1$ if the price of a face-to-face appointment is 25% higher than the price of an online appointment for individual i. $HP_i = 0$ if both channels have equal prices. $IM1_i = 1$ if individual i sees the infection risk nudge message, $IM1_i = 0$ otherwise. We include the interaction effect of price and nudge in the model with $HP_i \times IM1_i$. This interaction term equals one if there is a price difference and a nudge message.

Table 4.4: Average scale results and age with standard deviations in parentheses, percentages of females and participants with previous online experiences in Study 1

Group	PROS	RISK	OCAS	FCAS	Age	Female%	Exp%
Control (C1)	5.485	4.640	4.868	5.707	21.683	61%	28%
	(0.871)	(0.970)	(1.052)	(1.027)	(1.351)		
Higher Price (HP)	5.646	4.579	4.928	5.861	21.458	67%	25%
	(0.762)	(1.019)	(1.203)	(1.063)	(1.352)		
Infection Message (IM1)	5.672	4.577	4.895	5.711	21.703	51%	23%
	(0.841)	(0.949)	(1.258)	(0.994)	(1.450)		
Interaction (HP × IM1)	5.556	4.519	4.861	5.711	21.542	65%	28%
	(0.998)	(0.938)	(1.137)	(1.245)	(1.342)		
Grand Average	5.587	4.581	4.887	5.746	21.600	61%	26%
Cronbach's alpha	0.733	0.718	0.885	0.928	-	-	-

$RISK_i$ represents the average score of the COVID-19 risk perception scale, $PROS_i$ represents the average score of the prosociality scale, and finally, $OCAS_i$ and $FCAS_i$ represent the average scores of the scales for the attitude toward receiving online and face-to-face counseling, respectively. $RISK_i \times IM1_i$ accounts for the moderating effect of risk perception on the infection message. Finally, X_i is a vector consisting of controls of age, gender, and a binary variable measuring whether individual i has had an online appointment in the past.

The results of the model in (4.1) are presented in Table 4.5. Providing a negatively framed infection message associated with making a face-to-face appointment significantly increases the percentage of online appointments chosen, and Hypothesis 1a is supported. A price difference of 25% between the channels does not significantly increase the percentage of online appointments chosen, and Hypothesis 2 is not supported. The interaction effect is not significant, indicating the price difference has no impact on the effect of the infection message. RISK has a significant and positive relationship with the online channel preferences. There is no moderating effect of RISK on the infection message. Consequently, Hypotheses 5a and 5b

Table 4.5: Study 1. Results of the logistic regression model in (4.1). The data includes participants who gave correct answers to at least one comprehension check. RISK is mean-centered to eliminate multicollinearity and reduce pairwise correlations.

Dependent Variable: Channel Choice	β	std. error	p-value
Higher Price (HP)	0.401	0.348	0.250
Infection Message (IM1)	0.915	0.348	0.009
Higher Price × Infection Message (HP × IM1)	−0.573	0.492	0.245
RISK	0.489	0.196	0.013
RISK × Infection Message (RISK × IM1)	0.015	0.267	0.955
OCAS	0.175	0.130	0.178
FCAS	−0.476	0.145	0.001
PROS	0.089	0.154	0.565
Age	−0.043	0.092	0.642
Female	0.160	0.269	0.553
Online Experience	0.205	0.284	0.472
Intercept	1.418	2.280	0.534

are not supported under Study 1. FCAS has a significant and negative relationship with patients' online channel preferences. Patients with higher PROS and OCAS have chosen the online channel more, as directionally expected, yet the regression results show no significant effects. We do not observe any effects of age, gender, or previous online experience.

We did not include the prosociality scale in Studies 2, 3, and 4. In Study 2, the infection risk message has no prosocial component. In Studies 3 and 4, we focus on the infection risk elimination and convenience dimensions of the telemedicine channel. Although the infection message in these studies includes the risk elimination for family and friends, we do not measure PROS due to its ineffectiveness in Study 1.

Discussion

In Study 1, we test the effectiveness of an infection message and a price difference between the channels in increasing the online channel uptake under an epidemic scenario. When the prices of the two channels are equal, showing an infection message associated with making a face-to-face appointment (negative framing) significantly increases the percentage of online appointments chosen. Although offering a 25% price difference in favor of the online channel increases the percentage of online appointments chosen compared to the control group on average, this effect is not significant. This result is in line with the study by Hoenink et al. (2020), which argues that a price change that is not communicated to the participants (non-salient) did not significantly increase healthy food purchases alone. A combination of a salient price increase on unhealthy products and a discount on healthy products leads to an increase in healthy food consumption. Our experimental design may qualify as a non-salient pricing strategy. We provide the information that the face-to-face channel has a 25% higher price than the online channel in the scenario, alongside other information. Yet, we do not show an additional message emphasizing the price difference. There may be other confounding factors leading to the ineffectiveness of our price difference, such as insurance considerations. The interaction of the infection message and the price difference is not significant, indicating that a 25% price difference does not have an impact on the effectiveness of the infection message in increasing telemedicine adoption. The risk perception of the participants does not moderate the effectiveness of the infection message on the online channel adoption. Finally, FCAS has a significant and negative effect on the online channel choice.

To run a robustness check, we test our model in (4.1) with data including participants who gave correct answers to both comprehension checks. Table J.2 shows that the significance of the infection message is robust.

4.2.2 Experiment 2: Infection Risk Messaging vs Wait Time Messaging

Study 1 tested the effectiveness of a price difference and an infection message in telemedicine adoption. The message aimed at increasing the infection risk perception of patients through a negative framing. The results of Study 1 showed that emphasizing infection risk for self and others significantly increases the percentage of patients choosing the online channel. In Study 2, we study a positively framed infection message that focuses on eliminating self-risks by making an online appointment. There are two reasons to change the message framing. First, negatively framed COVID-19 health messages increase anxiety compared to positively framed ones (Dorison et al. 2022). Consequently, healthcare providers may not want to use negative framing. Second, positive framing is more effective than negative framing in promoting preventive behavior (Gallagher and Updegraff 2012, Soofi et al. 2020). We approach making an online appointment as a preventive behavior against getting infected. In addition to the infection message, in Study 2, we explore another dimension: appointment wait time difference between the channels. Our focus is on a systems perspective, where the provider offers a shorter appointment wait time for the online channel as an outcome of its capacity management policy. The appointment wait time difference is presented within the scenario to all groups. In the appointment wait time message group, it is further highlighted with a message emphasizing that making an online appointment allows patients to see the doctor sooner, helping to prevent the deterioration of their health condition. The message uses a positive framing due to its focus on preventive behavior.

The appointment wait time difference is operationalized within the scenario. The earliest available appointment is after 1 week for the online channel and after 2 weeks for the face-to-face channel. For the online channel, the wait time has uncertainty, in which there is a risk of waiting more than a face-to-face appointment. With a 70% chance, the patient is treated virtually after 1 week; with a 30% chance, there is a need for a face-to-face follow-up appointment where the patient is treated after 3 weeks (1 week + 2 weeks). For the face-to-face appointment channel, there is no wait time uncertainty. The patient has a certain wait of 2 weeks to get treated. Consequently, the channel choice leads to observable appointment wait time differences (1, 2, or 3 weeks to get treated). We need to control for participants' wait time risk-taking behavior, which can influence channel choice. We use Question 1 of

Study 8 in Leclerc et al. (1995), which asks participants to choose between a certain wait of 60 minutes versus a 50% chance of waiting 30 minutes and a 50% chance of waiting 90 minutes. We adapted the duration in the two options to make them comparable to our scenario, where one option has a certain waiting time of 2 weeks, and another option has a probabilistic waiting time of 1 week versus 3 weeks with equal probability. We refer to this binary control variable as wait risk-taking and denote it with “WRT”.

Participants, Design, and Experimental Groups

Study 2 was conducted from 29 April to 12 May 2024. Of 313 participants with complete entries, 14 gave incorrect answers to both comprehension check questions. As part of our exclusion criterion, their data is removed. The final sample size is 299.

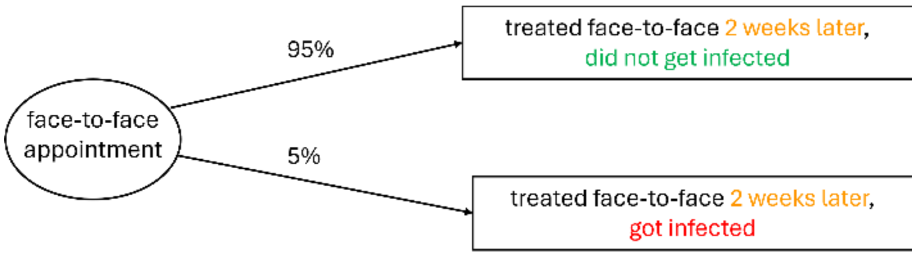
Study 2 has three experimental groups: control (C2), infection message (IM2), and wait time message (WM). The only difference between the control and message groups is the message shown to the participants before they make their channel choice. For the infection message group, the message is: “If you make an online appointment, you can eliminate physical interaction and prevent getting infected with the new virus”. For the wait time message group, the message is: “If you make an online appointment, you can see the doctor sooner and prevent a deterioration of your health condition”. Both messages are positively framed. They underline the different benefits of making an online appointment. The infection message focuses on the infection risk elimination dimension for self-risk, while the wait time message focuses on the appointment wait time reduction feature, preventing health condition deterioration. Table 4.6 summarizes the differences among the experimental groups.

Participants give consent to participate in the study. Different from Study 1, which announces the existence of a new variant of COVID-19, Study 2 announces a new highly contagious virus similar to SARS-CoV-2. This new virus impacts people of all ages, it spreads fast, and there are no effective vaccines. Instead of a new variant of COVID-19, to keep the scenario relevant for a possible new epidemic, we

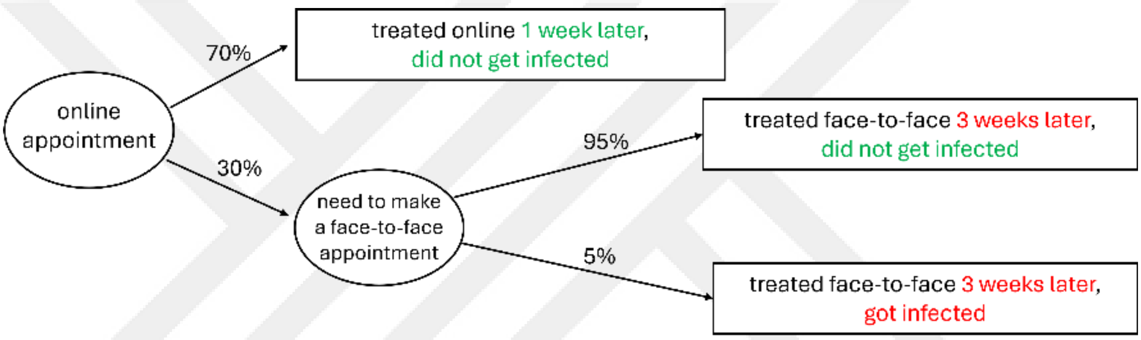
Table 4.6: The differences of the experimental groups in Study 2

Group	Message
Control (C2)	No message
Infection Message (IM2)	Message emphasizing the prevention of infection risk
Wait Time Message (WM)	Message emphasizing the prevention of health condition deterioration

announce a new virus. Next, the health scenario is presented: "Imagine that you are in your current state of health, but over the last week, you have been feeling dizzy and fatigued. You have tried several things yourself to remedy this problem but are not feeling any better". This scenario is similar to the ones used by Liu et al. (2018) and Liu and KC (2023). These symptoms are chosen to cover a wide range of illnesses and to present a condition that would have a high chance of effective virtual treatment. These symptoms can be perceived as non-urgent, but they would still impact the quality of life. Note that in Study 1, the health scenario had no details; it stated that participants had a health problem unrelated to COVID-19, and it was believed to be non-urgent. In Study 2, we make the health scenario more specific to make sure that participants have a similar idea about their health condition. After learning about the new virus and the health condition, participants choose between two appointment options: face-to-face and online. Both are described as being offered by the same doctor, having the same cost, and the same appointment duration. The trade-offs between the channels are infection risk for the face-to-face channel and revisit risk for the online channel. These trade-offs are illustrated in the experiment with Figure 4.2. Additionally, there is a difference between the appointment wait times. In determining the appointment wait time for the face-to-face option in the scenario, a 2022 survey of physician appointment wait times is taken into consideration (Merritt Hawkins 2022). For the online option, we base our wait time scenario on the literature on telemedicine appointment wait times being lower than the in-person appointment wait times (MAHSO 2021, Graetz et al. 2022, Tilley 2022, Pullyblank et al. 2024). In light of the literature, the earliest available appointment times are after 2 weeks for the face-to-face option and 1 week for the online option in our scenario.



(a) Face-to-face channel



(b) Online channel

Figure 4.2: Trade-offs for the two channels in Study 2

After reading the scenario and the trade-offs, the IM2 and WM groups see the related message. Next, the appointment channel decision is made. Following the decision, the wait risk-taking question is asked, followed by the COVID-19 risk perception scale and the value of online and face-to-face counseling scales. Then, information on age, gender, and previous online experience is collected. In the last screen, the participants learn the result of their appointment choice and how much they had to wait to get treatment, as given in Table 4.7. Additionally, for the participants who gave a correct answer to both comprehension checks, a screen is shared to announce that they are eligible for a lunch ticket.

Table 4.7: Appointment decisions, probabilities, and outcomes in Study 2

Decision	Probability	Outcome
Face-to-face	0.05	treated after 2 weeks, but get infected
Face-to-face	0.95	treated after 2 weeks, and do not get infected
Online	0.015	treated in the follow-up appointment after 3 weeks, but get infected
Online	0.285	treated in the follow-up appointment after 3 weeks, and do not get infected
Online	0.70	treated in the online appointment after 1 week, and do not get infected

Summary Statistics

Distribution of the 299 participants to the groups and their appointment choices are provided in Table 4.8. The ratio of participants who choose the online appointment option in the group IM2 is the highest one among the three groups, with 52.94%. It is followed by the group WM (46.94%). For the group C2, the online appointment percentage is 40.40%. We conduct Pearson Chi-square tests for the pairwise comparisons of the groups IM2 and WM with the group C2. The IM2 group has a higher percentage of online appointments chosen (p-value=0.075) compared to the group C2 under a significance level of $\alpha = 0.1$. The WM group is not significantly different from the group C2 regarding the percentage of online appointments chosen (p-value=0.355). The significance of the IM2 group is not robust in the data that includes participants who gave a correct answer to both comprehension checks (p-value=0.175).

Table 4.9 presents the averages and the standard deviations of the three scales (RISK, OCAS, FCAS) and age by group, as well as the percentage of appointment wait time risk takers (WRT), the percentage of females, and the percentage of participants with previous online experiences. The Cronbach's alpha values are also

Table 4.8: Groups and appointment channel choices in Study 2

Group	Face-to-face	Online	Total#	Online%
Control (C2)	59	40	99	40.404%
Infection Message (IM2)	48	54	102	52.941%
Wait Time Message (WM)	52	46	98	46.939%
Grand Total	159	140	299	46.823%

reported. Each scale can take any value between 1 and 7. One-way ANOVA results show no significant difference in scales among the three experimental groups (see Appendix J.3). For the WRT measure, Chi-square test results show a significant difference among the groups (see Appendix J.4). Pairwise Chi-square comparisons show that the wait risk-taking participants in the IM2 group are significantly higher than the C2 and WM groups (see Appendix J.5). This imbalance may be due to chance. An alternative explanation can be related to the resemblance of our scenario and the WRT measure. Specifically, we took the wait time durations in the scenario and the WRT measure the same (a certain wait of 2 weeks vs a wait of 1 week or a wait of 3 weeks) to increase the relevance of the control variable. However, we overlooked the possibility that this may have been interpreted as a consistency check, resulting in highly correlated responses. Participants who chose the online option in the experiment chose the risk-taking option in that question to be consistent with their choice. We keep WRT as a control variable in our analysis. To account for the possibility of the WRT measure being seen as a consistency check, we further analyze the model without it and discuss the results.

Model Specification and Results

The dependent variable O_i is a binary variable taking the value of 1 if individual i chooses the online channel and 0 if individual i chooses the face-to-face channel. Consequently, $\mathbf{P}(O_i = 1)$ denotes the probability of individual i choosing the online

Table 4.9: Average scale results and age with standard deviations in parentheses, percentages of wait time risk-takers, females, and participants with previous online experiences in Study 2

Group	WRT%	RISK	OCAS	FCAS	Age	Female%	Exp%
Control (C2)	39%	4.966	5.010	5.782	22.020	75%	36%
		(0.889)	(1.094)	(0.956)	(1.301)		
Infection Message (IM2)	64%	4.642	4.884	5.584	21.725	59%	31%
		(1.013)	(1.130)	(1.078)	(1.463)		
Wait Time Message (WM)	42%	4.767	4.898	5.592	21.827	60%	29%
		(1.019)	(1.157)	(0.984)	(1.407)		
Grand Average	49%	4.790	4.930	5.652	21.856	65%	32%
Cronbach's alpha	-	0.733	0.870	0.892	-	-	-

channel and $\mathbf{P}(O_i = 0)$ denotes the probability of individual i choosing the face-to-face channel. The logistic regression model used in Study 2 is as follows.

$$\begin{aligned} log\left(\frac{\mathbf{P}\left(O_i = 1\right)}{\mathbf{P}\left(O_i = 0\right)}\right) &= \beta_0 + \beta_1 IM2_i + \beta_2 WM_i + \beta_3 RISK_i \\ &+ \beta_4 RISK_i \times IM2_i + \beta_5 OCAS_i + \beta_6 FCAS_i + \beta_7 WRT_i + \beta_8 X_i \end{aligned} \tag{4.2}$$

$IM2_i = 1$ if participant i is in the infection message group, $WM_i = 1$ if participant i is in the wait time message group. If both $IM2_i$ and WM_i are zero, then, participant i is in the control group. $RISK_i$ is the average score of the COVID-19 risk perception scale for participant i. $RISK_i \times IM2_i$ measures the moderating impact of RISK on IM2. $OCAS_i$ and $FCAS_i$ are the average scores of participant i for the attitudes toward online and face-to-face counseling scales. WRT_i is 1 if participant i is a wait risk taker and 0 otherwise. Finally, X_i represents other controls of age, female dummy, and previous online experience dummy.

The results of the model in (4.2) are provided in Table 4.10. The message interventions are not significant. Hypotheses 1b and 3 are not supported. RISK is partially significant. There is no moderating effect of RISK on IM2. Hypotheses 5a and 5b are not supported. OCAS and FCAS significantly affect the preference

Table 4.10: Study 2. Results of the logistic regression model in (4.2). The data includes participants who gave correct answers to at least one comprehension check. RISK is mean-centered to eliminate multicollinearity and reduce pairwise correlations.

Dependent Variable: Channel Choice	β	std. error	p-value
Infection Message (IM2)	0.251	0.336	0.456
Wait Time Message (WM)	0.287	0.329	0.382
RISK	0.321	0.192	0.094
RISK $\times$ Infection Message (RISK $\times$ IM2)	-0.474	0.297	0.110
OCAS	0.462	0.145	0.001
FCAS	-0.438	0.164	0.007
WRT	1.703	0.280	< 0.001
Age	0.216	0.101	0.033
Female	-0.242	0.293	0.408
Online Experience	-0.057	0.286	0.843
Intercept	-5.543	2.469	0.025

for the online channel in opposite directions. Participants with a higher OCAS are more likely to choose the online channel, while participants with a higher FCAS are less likely to choose the online channel. WRT is significant and positive. This shows that wait time risk takers choose the online channel more. Finally, age has a positive and significant effect on the telemedicine channel choice.

We analyze the model in (4.2) without the WRT measure, and the results are reported in Table 4.11. In this model, IM2 is partially significant. There is a negative moderating effect of RISK on the infection message. The significances of OCAS, FCAS, and age do not change.

Table 4.11: Study 2. Logistic regression results for appointment channel choice as formulated in (4.2) without the WRT variable.

Dependent Variable: Channel Choice	β	std. error	p-value
Infection Message (IM2)	0.586	0.309	0.058
Wait Time Message (WM)	0.310	0.305	0.310
RISK	0.304	0.175	0.083
RISK × Infection Message (RISK × IM2)	−0.581	0.274	0.034
OCAS	0.397	0.134	0.003
FCAS	−0.528	0.151	< 0.001
Age	0.236	0.093	0.011
Female	−0.171	0.271	0.526
Online Experience	0.195	0.264	0.459
Intercept	−4.555	2.263	0.044

Discussion

In Study 2, we test the effectiveness of two messages in increasing patients' online channel preferences during times of a new infectious virus similar to SARS-CoV-2. Both messages are positively framed. The infection message emphasizes the elimination of the infection risk via the online channel for oneself, while the wait time message focuses on the reduction of the appointment wait time via the online channel and, consequently, the prevention of the health condition from getting worse. Under both messages, the appointment wait time difference between the channels is embedded in the scenario provided to the participants. The appointment wait time difference is an important factor in determining the channel choice, which may have shifted participants to choose the online channel on its own without the need for being nudged. We observe that the positively framed wait time message is not effective in shifting patient demand toward the online channel. For the positively framed infection message, the model with the WRT measure shows no significance.

Table 4.12: Study 2. Results of the logistic regression model in (4.2) after weighting the data with the inverse probability weighting method.

Dependent Variable: Channel Choice	β	std. error	p-value
Infection Message (IM2)	0.192	0.179	0.282
Wait Time Message (WM)	0.289	0.175	0.098
RISK	0.351	0.101	< 0.001
RISK $\times$ Infection Message (RISK $\times$ IM2)	-0.703	0.161	< 0.001
OCAS	0.431	0.080	< 0.001
FCAS	-0.546	0.089	< 0.001
Age	0.239	0.054	< 0.001
Female	-0.108	0.158	0.492
Online Experience	0.146	0.151	0.333
Intercept	-4.582	1.297	< 0.001

As discussed in Section 4.2.2, the WRT measure can be biased. Table 4.11 shows the regression results without the WRT measure. In this model, the IM2 and RISK become partially significant. The negative and significant coefficient of the RISK and IM2 interaction shows that the infection message is more effective in patients with lower RISK. OCAS and FCAS are significant with and without the WRT measure. Finally, to account for the imbalance in the WRT measure among the groups, we used the inverse probability weighting method. This method creates a pseudo-population where the group assignment is independent of the WRT measure. The results are shared in Table 4.12. Similar to the model without the WRT measure in the unweighted data (Table 4.11), we observe significant results for RISK, interaction of RISK and IM2, OCAS, and FCAS. Unlike the model in Table 4.11, in Table 4.12, we observe a partial significance for the WM while the partial significance of IM2 disappears.

We test our model in (4.2) with data including participants who gave correct answers to both comprehension checks. Table J.6 shows that the infection message, the wait time message, and the interaction of risk perception and infection message are insignificant. Another robustness check is run for the model without WRT, and the results are provided in Table J.7. The significance of the interaction of risk perception and infection message is not robust. The partial significance of the infection message disappears. Finally, in Table J.8, we test the robustness of the results in the weighted data. The partial significance of WM disappears. The interaction of RISK and IM2 becomes partially significant. The significances of the other variables are robust.

The results of the unweighted model without WRT and the weighted model (inverse probability weighting) show differences in the significances of the infection message and wait time message. It is hard to conclude which model reflects the real relationship between the nudge messages and the telemedicine channel choice. To address the concerns regarding WRT in Study 2, in Study 3, we use an updated version of this measure by changing the durations in the two alternatives presented for the wait time question to a certain wait of 6 days versus an equal probability of waiting 3 days and 9 days.

4.2.3 Experiment 3: Infection Risk Messaging vs Convenience Messaging

In Study 2, the appointment wait time difference between the channels was taken as an outcome of the provider's capacity management policy, where the channels had different earliest available appointment times. When the wait time difference is embedded in the scenario, nudge messages do not have any significant implications for channel choice. In a setting where the healthcare provider offers similar appointment wait times for the channels, there can still be a wait time difference due to patients' logistical considerations (Graetz et al. 2022). Study 3 takes this approach and focuses on the patient's perspective in terms of appointment wait times, which we refer to as convenience. The convenience message emphasizes the ease of fitting an online appointment into a patient's schedule (elimination of transportation-related concerns leading to easier planning), which allows the patient to see the doctor sooner. In addition to the convenience message, there is a positively framed infec-

Table 4.13: The differences of the experimental groups in Studies 3 and 4

Group	Message
Control (C3)	No message
Infection Message (IM3)	Message underlining the prevention of infection risk
Convenience Message (CM)	Message underlining the ease of scheduling and seeing the doctor sooner

tion message emphasizing the elimination of self-risk and risk for others by making an online appointment.

Participants, Design, and Experimental Groups

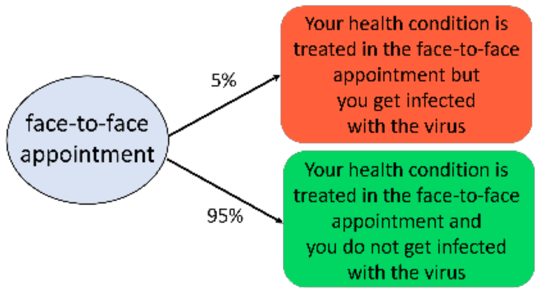
Study 3 was preregistered to AsPredicted (#198238) and conducted on 11-24 November 2024. Of 385 participants with complete entries, 26 participants gave incorrect answers to both comprehension check questions. As part of our exclusion criterion, their data is removed. The final sample size is 359.

Study 3 has three experimental groups: control (C3), infection message (IM3), and convenience message (CM). The only difference between the control group and the two message groups is the message shown to the participants before they make their channel choice. For the infection message group, the message is: "You can eliminate physical interaction in an online appointment. Therefore, you may save yourself and your family and friends from getting infected with the new virus". For the convenience message group, the message is: "You can fit an online appointment into your schedule more easily than a face-to-face appointment. Therefore, you may see the doctor sooner with an online appointment than a face-to-face one". Both messages are positively framed. In Study 2, the infection message focused on the self-risk to see its individual impact. In Study 3, the infection message emphasizes the risk for others in addition to the self-risk. Table 4.13 summarizes the differences among the experimental groups.

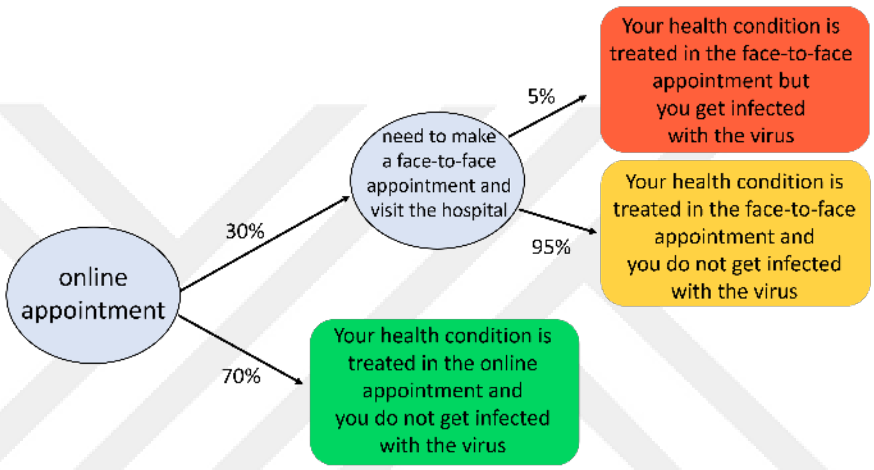
Participants provide their consent to participate in the experiment. They read the virus scenario, which states the existence of a new virus similar to SARS-CoV-2.

This new virus is stated to impact people of all ages and to spread fast, and there are no effective vaccines. For the same reasons as in Study 2, the scenario is changed to a new virus instead of a new variant of COVID-19. Next, the health scenario is provided: "Imagine that you are in your current state of health, but over the last week, you have been feeling fatigued, slightly dizzy, and having difficulty sleeping. You have tried several things yourself to remedy this problem but are not feeling any better". Different than Study 2, in Study 3, we have an additional symptom in the scenario, which is having difficulty sleeping. This allows the health condition to cover a larger set of possible diseases, increasing its generalizability further. In Study 3, we want to measure participants' transportation-related efforts to see a doctor. To eliminate the choice of seeing the doctor on campus and to ensure some variability in travel time and travel mode, the scenario states that "The university's health center suggests you see a doctor at a hospital." We further asked participants to imagine the hospital they would visit in the given case. Participants are asked to think about their schedules for the next two weeks. The scenario states that time slots are available for both channels for the next two weeks. Then, they are given two appointment options: face-to-face and online. Both channels are stated to be offered by the same doctor, are fully covered by their insurance, and have the same appointment duration. There is a 5% infection risk for the face-to-face channel and a 30% revisit risk for the online channel. In the experiment, these trade-offs are illustrated with Figure 4.3.

After reading the scenario and the trade-offs, the participants in the message groups read the related message. Next, the appointment channel decision is made. Then, transport-related questions are asked. The first question is, "If you wanted to physically visit the hospital, what would be your mode of travel?". There are four possible answers: walking, private car, public transport, and transport services (taxi, Uber, etc.). The second question is, "Considering your mode of travel, how much time would you need to get there?". There are three possible answers: <1 hour, 1 hour $-$ 2 hours, and $>$ 2 hours. Next, they are asked whether they have experienced an online appointment to account for a previous online experience. After



(a) Face-to-face channel



(b) Online channel

Figure 4.3: Trade-offs for the two channels in Study 3

these questions, participants complete three scales: COVID-19 risk perception and the values of online and face-to-face counseling. Following the scales, the wait time risk-taking question is asked. Finally, information on age and gender is collected. In the last screen, participants learn the outcome of their appointment choice (see Table 4.2). Additionally, for the participants who gave a correct answer to both comprehension checks, a screen is shared to announce that they are eligible for a gift card.

Summary Statistics

Distribution of the 359 participants to the groups and their appointment choices are provided in Table 4.14. The ratio of participants who choose the online appoint-

Table 4.14: Groups and appointment channel choices in Study 3

Group	Face-to-face	Online	Total#	Online%
Control (C3)	69	53	122	43.443%
Infection Message (IM3)	59	61	120	50.833%
Convenience Message (CM)	47	70	117	59.829%
Grand Total	175	184	359	51.253%

ment option in group C3 is 43.44%. For the group IM3, the ratio is 50.83%. The group CM is the highest one among the three groups, with 59.83%. We conduct Pearson Chi-square tests for the pairwise comparisons of the groups IM3 and CM with the group C3. The CM group has a higher percentage of online appointments chosen compared to the group C3 (p-value=0.011). The IM3 group is not significantly different from the C3 group in terms of the percentage of online appointments chosen (p-value=0.249). The significance of the CM group is robust to the data that includes participants who gave a correct answer to both comprehension checks (p-value=0.012).

Table 4.15 presents the averages and standard deviations of the three scales (RISK, OCAS, FCAS), and age by group, as well as the percentage of wait time risk takers (WRT), the percentage of females, and the percentage of participants with previous online experiences. The Cronbach's alpha values are also reported. Each scale can take any value between 1 and 7. None of the scales are significantly different among the groups (see Appendix J.9). Chi-square test results show that there is no significant difference in WRT among the groups (see Appendix J.10). For the travel-related questions, the results show that most of the participants travel to the hospital in a private car (67%), and their travel time is less than 1 hour (75%).

Table 4.15: Average scale results and age with standard deviations in parentheses, percentages of wait time risk-takers, females, and participants with previous online experiences in Study 3

Group	WRT%	RISK	OCAS	FCAS	Age	Female%	Exp%
Control (C3)	50%	4.947	4.833	5.857	21.549	60%	23%
		(0.985)	(1.148)	(0.874)	(1.267)		
Infection Message (IM3)	53%	5.006	4.872	5.673	21.483	64%	18%
		(0.999)	(1.315)	(1.122)	(1.390)		
Convenience Message (CM)	43%	5.073	4.771	5.738	21.650	63%	22%
		(0.921)	(1.230)	(0.992)	(1.410)		
Grand Average	49%	5.007	4.826	5.757	21.560	62%	21%
Cronbach's alpha	-	0.747	0.878	0.882	-	-	-

Model Specification and Results

The dependent variable O_i is a binary variable taking the value of 1 if individual i chooses the online channel and 0 if individual i chooses the face-to-face channel. Consequently, $\mathbf{P}(O_i = 1)$ denotes the probability of individual i choosing the online channel and $\mathbf{P}(O_i = 0)$ denotes the probability of individual i choosing the face-to-face channel. The logistic regression model in Study 3 is as follows.

$$log\left(\frac{\mathbf{P}\left(O_i = 1\right)}{\mathbf{P}\left(O_i = 0\right)}\right) = \beta_0 + \beta_1 IM3_i + \beta_2 CM_i + \beta_3 RISK_i + \beta_4 RISK_i \times IM3_i$$
$$+ \beta_5 Travel_i + \beta_6 Travel_i \times CM_i + \beta_7 OCAS_i + \beta_8 FCAS_i + \beta_9 X_i \quad (4.3)$$

$IM3_i = 1$ if participant i is in the infection message group, $CM_i = 1$ if participant i is in the convenience message group. If both $IM3_i$ and CM_i are zero, then participant i is in the control group. $RISK_i$ is the average score of the COVID-19 risk perception scale for participant i. $RISK_i \times IM3_i$ measures the moderating effect of RISK on IM3. $Travel_i$ takes the value of 1 if individual i has a travel time of less than 1 hour to a hospital. $Travel_i \times CM_i$ measures the moderating effect of travel time on CM. $OCAS_i$ and $FCASi$ are the average scores of participant i for the attitudes toward online and face-to-face counseling scales. Finally, X_i is the set of control variables and includes a binary variable indicating wait time risk-taking, a binary variable indicating travel mode being a private car, a binary variable measuring whether an individual has previous experience with the online channel, a binary variable indicating being female, and age.

The results of the model in (4.3) are provided in Table 4.16. The positively framed infection message, emphasizing eliminating risk for self and others by making an online appointment, is insignificant. Hypothesis 1c is not supported. The convenience message is significant. Hypothesis 4 is supported. RISK is not significant. The moderating effect of RISK on IM3 shows that the infection message is more effective in patients with higher RISK scores. Hypothesis 5a is supported, Hypothesis 5b is not supported. The moderating effect of travel time on the convenience message shows that patients who spend less time traveling to the hospital are less affected by the convenience message. Hypothesis 6a is supported, Hypothesis 6b is not supported. OCAS and FCAS significantly affect the preference for the online channel in opposing directions. Participants with higher OCAS are more likely to choose the online channel, while participants with higher FCAS are less likely to choose the online channel. Finally, there is no effect of wait time risk-taking behavior, age, gender, online experience, travel time, or using a private car on the telemedicine channel choice.

Discussion

In Study 3, we test the effectiveness of two message interventions, both positively framed. One tests the effectiveness of the message emphasizing the elimination of the infection risk for self and others, and the other tests the effectiveness of the message emphasizing seeing the doctor sooner (convenience). The convenience message intervention that underlines the ease of fitting an online appointment for patients into their schedule is effective in increasing online channel adoption. The effectiveness of the convenience message is amplified for patients who are located further away from the hospital. This shows that the travel burden is a major consideration for patients regarding the convenience of the online channel. The convenience mes-

Table 4.16: Study 3. Results of the logistic regression model in (4.3). The data includes participants who gave correct answers to at least one comprehension check. RISK and Travel Time are mean-centered to eliminate multicollinearity and reduce pairwise correlations.

Dependent Variable: Channel Choice	β	std. error	p-value
Infection Message (IM3)	0.272	0.272	0.316
Convenience Message (CM)	0.647	0.279	0.020
RISK	-0.012	0.153	0.936
RISK × Infection Message (RISK × IM3)	0.507	0.255	0.047
Travel Time	0.456	0.354	0.198
Travel Time × Convenience Message (Travel × CM)	-1.423	0.585	0.015
OCAS	0.253	0.108	0.019
FCAS	-0.312	0.134	0.020
WRT	0.294	0.229	0.199
Age	0.112	0.084	0.183
Female	-0.136	0.243	0.574
Online Experience	0.442	0.278	0.111
Private Car	-0.471	0.262	0.073
Intercept	-1.941	1.964	0.323

sage aligns with their preferences for the online channel, which increases its impact. Patients who live near the hospital do not have much of the burden of traveling for a face-to-face appointment. Consequently, the convenience dimension of online appointments has little value for them. In this context, the indifference between the options does not lead the nudge message to be more effective, contrary to the findings of Bonander et al. (2023) and Venema et al. (2020).

For the positively framed infection message emphasizing the elimination of risk for the patients and their family members and friends, we do not see a significant impact on the online channel choice. Infection risk perception of the patients (RISK) also does not have a significant effect on the channel choice. However, unlike Study 2 (without WRT), in Study 3, the infection message is significantly more effective in patients with higher infection risk perceptions. A significant difference between these studies is how the appointment wait time difference is communicated. In Study 2, this difference is embedded in the scenario. This may have led participants with higher health anxieties to choose the online channel to be able to see the doctor sooner. Those participants may also have a higher RISK score as they would be anxious about an infectious virus, too. This may have led participants with higher RISK scores to choose the online channel, independent of the nudge message (ceiling effect). Consequently, in Study 2, the nudge message is more effective in patients with lower RISK scores. However, in Study 3, the wait time difference is not forced by the provider. Instead, it depends on the patient's schedule. Consistent with this, there is no significant relationship between RISK and online choice. In this case, patients with higher RISK scores are affected more by the infection message. Another difference between the two studies is the content of the infection message. Study 3 includes the risk for others, while Study 2 only has the self-risk. This aspect in Study 3 may make it more effective in patients who are aware of the risks of making a face-to-face appointment. A final observation on the regression results for Study 3 is that OCAS and FCAS significantly impact the channel choice in opposite directions, as expected. Accounting for these inherent attitudes toward the channels is important. The convenience message is effective when we control for these factors.

To run a robustness check, we test our model in (4.3) with data including participants who gave correct answers to both comprehension checks. Table J.11 shows that the convenience message intervention effectively increases the online channel adoption of participants in both specifications. Unlike Study 2, in Study 3, the significance of the interaction of risk perception and infection message is robust. Finally, the significance of the interaction between travel time and convenience message is not robust.

4.2.4 Experiment 4 (Prolific): Infection Risk Messaging vs Convenience Messaging

The convenience message in Study 3 has the advantage of generalizability beyond the epidemics. Its positive frame has the benefit of not inducing negative emotions. After seeing its potential in increasing the online channel adoption of the participants in Study 3, we want to test it in a different sample in Study 4. We test the same hypotheses, yet, instead of university students, we use a subject pool of participants in Prolific from various ages and educational backgrounds from the United States. This allows us to check whether different demographics, such as age, educational background, and having an online appointment experience, change the results of Study 3. Instead of an epidemic scenario, we provide information on respiratory virus seasons from the Centers for Disease Control and Prevention (CDC) (Centers for Disease Control and Prevention 2024a,b). This allows the results to be further generalized and increases the validity of our manipulation.

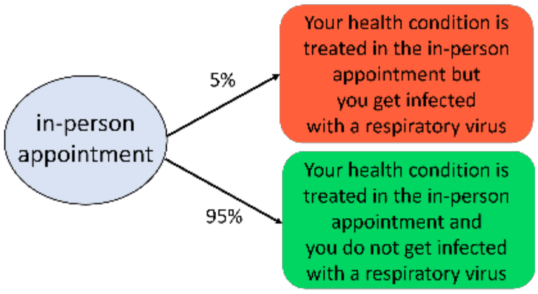
Participants, Design, and Experimental Groups

Study 4 was preregistered to AsPredicted (#218612) and conducted on 20-21 March, 2025. The prescreening criteria for the participant pool consisted of the current country of residence being the United States, having an approval rate of 95-100, and having at least 20 previous submissions. The sample size was 743.

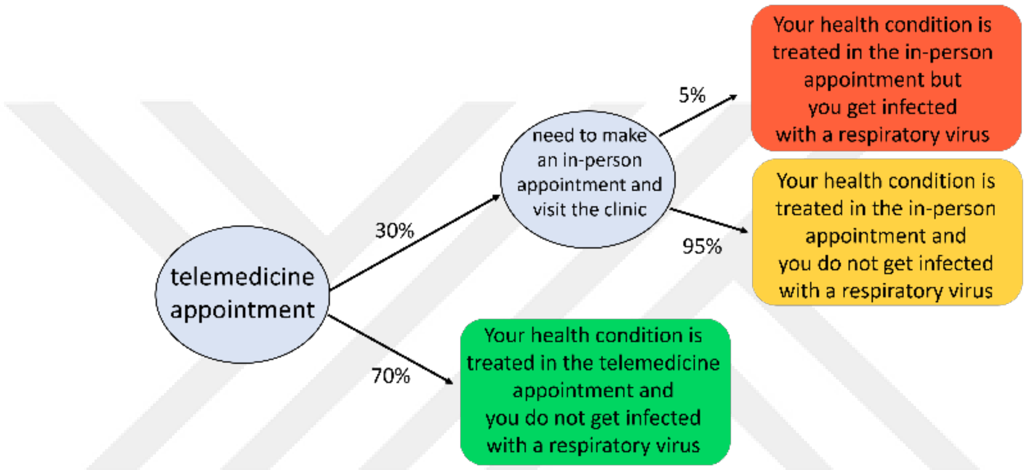
Study 4 has three experimental groups: control (C4), infection message (IM4), and convenience message (CM2). In the infection message group, participants see the following message before their channel choice: "There is no physical interaction in a telemedicine appointment. This will protect you and your family from getting infected with a respiratory virus". For the convenience message group, the message is as follows: "It is easier to fit a telemedicine appointment into a busy schedule than an in-person appointment. As a result, you may see the doctor sooner with a telemedicine appointment than with an in-person one". Both messages are positively framed, and the infection message considers risk for self and others. Table 4.13 summarizes the differences among the experimental groups.

Participants provide consent to participate in the experiment. After the introduction, the same health scenario in Study 3 is given in Study 4: "Imagine that you are in your current state of health, but over the last week, you have been feeling fatigued, slightly dizzy, and having difficulty sleeping. You have tried several things yourself to remedy this problem but are not feeling any better". Next, the participants are asked to consider the healthcare facility that they visit regularly to see a primary care physician (PCP). It is stated that there are available time slots for the next two weeks starting from tomorrow. Participants are encouraged to think about their schedule for the next two weeks. Then, they are given two options: telemedicine versus in-person. It is stated that their regular healthcare facility offers both options. Under both options, they will spend the same amount of time with the doctor. They are asked to assume that their insurance offers equal coverage, and they pay the same amount whether they choose a telemedicine or an in-person appointment. Next, the first attention check question is asked (see Appendix I). If a participant gives an incorrect answer to this question, a warning screen is shared that states: "You have failed the first attention check! You will be rejected if you fail one more attention check question!". Different from previous studies, there is no virus scenario in Study 4. Instead, in the in-person channel information screen, the following information is shared: "According to the Centers for Disease Control and Prevention (CDC), fall, winter, and early spring are the seasons for respiratory viruses such as influenza (flu), COVID-19, respiratory syncytial virus (RSV), and human metapneumovirus (HMPV)". This allows us to keep the disease information general and applicable to various respiratory viruses. As is the case in other studies, there is a 5% infection risk for the in-person channel and a 30% revisit risk for the telemedicine channel. In the experiment, these trade-offs are illustrated with Figure 4.4.

After reading the scenario and trade-offs, there is a second attention check question (see Appendix I). As an exclusion criterion, we planned to terminate the experiment for participants who answered both attention checks incorrectly. All participants passed at least one attention check question, and nobody was excluded. Next, the participants in the message groups see the related message. Then, they



(a) In-person channel



(b) Telemedicine channel

Figure 4.4: Trade-offs for the two channels in Study 4

make their channel choice. Following the channel choice, there is a comprehension check question (see Appendix H.4). The participants who gave a correct answer to the comprehension check question are paid a bonus. Next, the travel mode (walking, private or rental car, public transport, transport services (Taxi, Uber, Lyft, etc.)), travel time ($<$ 30 minutes, 30 minutes $-$ 1 hour, 1 hour $-$ 2 hours, $>$ 2 hours), and previous online experience (yes, no) is asked. After these questions, the participants are asked to complete three scales: RISK, OCAS, and FCAS. Following the scales, the WRT is asked. Finally, information on age, gender (female, male, another identity, prefer not to say), and education (less than high school, high school or equivalent, some college, undergraduate degree, graduate degree, doctorate degree) is collected. The last screen shares the outcome of the participant's channel

Table 4.17: Groups and appointment channel choices in Study 4

Group	In-person	Telemedicine	Total#	Telemedicine%
Control (C4)	153	94	247	38.057%
Infection Message (IM4)	134	115	249	46.185%
Convenience Message (CM2)	128	119	247	48.178%
Grand Total	415	328	743	44.145%

choice (see Table 4.2).

Summary Statistics

Distribution of the 743 participants to the groups and their appointment choices are provided in Table 4.17. The ratio of participants who chose the telemedicine appointment option in group C4 is 38.06%. For the group IM4, the ratio is 46.18%. The group CM2 is the highest one among the three groups, with 48.18%. We conduct Pearson chi-square tests for the pairwise comparison of the groups IM4 and CM2 with the group C4. The CM2 group has a higher percentage of telemedicine appointments chosen compared to the group C4 (p-value=0.023). The IM4 group is partially significantly different from the group C4 regarding the percentage of telemedicine appointments chosen (p-value=0.067). The CM2 group has partially significant Chi-square results for the data of participants who gave a correct answer to the comprehension check question (p-value=0.058). For the same data, the IM4 group is not significant (p-value=0.193).

Table 4.18 presents the averages and standard deviations of the three scales (RISK, OCAS, FCAS), and age by group, as well as the percentage of wait time risk takers (WRT), the percentage of females, the percentage of participants with previous online appointment experiences (Exp), and the percentage of participants with graduate or doctorate degree (Edu). The Cronbach's alpha values are also reported. Each scale can take any value between 1 and 7. None of the scales significantly differ among the groups (see Appendix J.12). Chi-square test results

Table 4.18: Average scale results and age with standard deviations in parentheses, percentages of wait time risk-takers, females, participants with previous online appointment experiences, and graduate or doctorate degree in Study 4

Group	WRT%	RISK	OCAS	FCAS	Age	Female%	Exp%	Edu%
Control	42%	4.490	5.215	5.594	41.449	58%	70%	23%
(C4)		(1.340)	(1.237)	(1.065)	(14.132)			
Infection Message	48%	4.251	5.241	5.527	40.325	59%	65%	20%
(IM4)		(1.296)	(1.253)	(1.169)	(14.323)			
Convenience Message	38%	4.269	5.158	5.632	40.551	57%	64%	25%
(CM2)		(1.223)	(1.250)	(1.038)	(14.643)			
Grand Average	43%	4.336	5.205	5.584	40.774	58%	66%	23%
Cronbach's alpha	-	0.832	0.922	0.919	-	-	-	-

show that there is no significant difference in WRT among the groups (see Appendix J.13). For the travel-related questions, the results show that most participants travel to the hospital with a private or rental car (83%), and their travel time is less than 30 minutes (71%).

Model Specification and Results

The dependent variable O_i is a binary variable taking the value of 1 if individual i chooses the telemedicine channel and 0 if individual i chooses the in-person channel. Consequently, $\mathbf{P}(O_i = 1)$ denotes the probability of individual i choosing the telemedicine channel and $\mathbf{P}(O_i = 0)$ denotes the probability of individual i choosing the in-person channel. The logistic regression model in Study 4 is as follows.

$$log\left(\frac{\mathbf{P}\left(O_i = 1\right)}{\mathbf{P}\left(O_i = 0\right)}\right) = \beta_0 + \beta_1 IM4_i + \beta_2 CM2_i + \beta_3 RISK_i + \beta_4 RISK_i \times IM4_i$$
$$+ \beta_5 Travel_i + \beta_6 Travel_i \times CM2_i + \beta_7 OCAS_i + \beta_8 FCAS_i + \beta_9 X_i \qquad (4.4)$$

$IM4_i = 1$ if participant i is in the infection message group, $CM2_i = 1$ if participant i is in the convenience message group. If both $IM4_i$ and $CM2_i$ are zero, then participant i is in the control group. $RISK_i$ is the average score of the COVID-19 risk perception scale for participant i. $RISK_i \times IM4_i$ measures the moderating effect of RISK on IM4. $Travel_i$ takes the value of 1 if individual i has a travel time of less than 30 minutes to a healthcare facility. $Travel_i \times CM2_i$ measures the moderating effect of travel time on CM2. $OCAS_i$ and $FCASi$ are the average scores of participant i for the attitudes toward online and face-to-face counseling scales. Finally, X_i is the set of control variables and includes a binary variable indicating wait time risk-taking (WRT), a binary variable measuring whether an individual has previous experience with the telemedicine channel (Exp), a binary variable indicating travel mode being a private car, a binary variable indicating being female, a binary variable indicating having a graduate or doctorate degree (Edu).

The results of the model in (4.4) are provided in Table 4.19. The positively framed infection message, emphasizing eliminating risk for self and others by making a telemedicine appointment, is significant. Hypothesis 1c is supported. The convenience message is also significant. Hypothesis 4 is supported. RISK is partially significant. There is no moderating effect of RISK on IM4. Hypotheses 5a and 5b are not supported. Travel time is significant, indicating that participants who reach the healthcare facility in less time choose the telemedicine option less. There is no moderating effect of travel time on the convenience message, and Hypotheses 6a and 6b are not supported. OCAS and FCAS significantly affect the preference for the telemedicine channel in opposing directions. Participants with higher OCAS are more likely to choose the telemedicine channel, while participants with higher FCAS are less likely to choose the telemedicine channel. WRT is positive and significant, indicating that wait risk-takers choose the telemedicine option more. Previous online appointment experience has a significant and positive impact on the telemedicine channel choice. There is no age, gender, private car use, or education effect.

Discussion

In Study 4, the participant pool consisted of Prolific participants in the United States with various demographics. Although we tested the same hypotheses as in

Table 4.19: Study 4. Results of the logistic regression model in (4.4). RISK and Travel Time are mean-centered to eliminate multicollinearity and reduce pairwise correlations.

Dependent Variable: Channel Choice	β	std. error	p-value
Infection Message (IM4)	0.386	0.195	0.048
Convenience Message (CM2)	0.603	0.196	0.002
RISK	0.142	0.079	0.073
RISK × Infection Message (RISK × IM4)	−0.060	0.131	0.645
Travel Time	−0.423	0.212	0.047
Travel Time × Convenience Message (Travel × CM2)	0.454	0.365	0.214
OCAS	0.510	0.091	< 0.001
FCAS	−0.419	0.097	< 0.001
WRT	0.512	0.160	0.001
Age	0.006	0.006	0.321
Female	−0.055	0.162	0.732
Online Experience	0.551	0.173	0.001
Private Car	0.006	0.215	0.977
Higher Education	−0.045	0.191	0.814
Intercept	−1.694	0.550	0.002

Study 3, we made several changes in Study 4 to make the experiment reliable for the pool. First, instead of a new virus scenario, we provide information on the respiratory virus seasons indicated by the CDC. Second, we change the wording slightly in several screens without changing the main theme (instead of online, we use the word telemedicine, etc.).

Study 4 shows that both infection message and convenience message interventions are effective in increasing telemedicine channel choice. Study 4 provides additional evidence on the significance of the convenience message and attitudes toward online and face-to-face counseling scales in Study 3. Finding a significant impact of the convenience message in both studies with different participant pools from varying backgrounds increases the validity of the convenience message intervention as an effective tool in patient demand management. Additionally, in Study 4, infection risk perception of the patients has a partially significant and positive impact on the telemedicine channel choice. Having a travel time of less than 30 minutes to a healthcare facility leads participants to choose the telemedicine channel more. Consistent with the telemedicine option, which has an uncertainty in the appointment wait times (due to the in-person follow-up risk), wait time risk-takers choose the telemedicine option significantly more. We also observe a positive impact of having prior online appointment experience on the telemedicine choice, consistent with the literature (Reed et al. 2020).

Unlike Study 3, in Study 4, we observe no moderating effect of infection risk perception on the telemedicine channel choice. Recall that Study 3 has an epidemic scenario of a new virus similar to SARS-CoV-2. In Study 4, there is no epidemic scenario; there is information from the CDC website on the respiratory virus seasons. The risk perception scale questions are about COVID-19. That could result from the difference between the significances of the interaction of risk perception and infection message in these studies. In Study 4, travel time does not moderate the convenience message, which differs from Study 3. This can be the result of having participants from different countries with varying traffic conditions, where the impact of travel time on the convenience of telemedicine can change. Although the moderation of travel time and the convenience message in Study 3 is significant, it is not robust to the sample of participants who gave a correct answer to both comprehension checks.

For a robustness check, we test our model in (4.4) with data including participants who gave a correct answer to the comprehension check. Table J.14 shows that the significance of the convenience message in increasing the telemedicine channel adoption of participants is robust. The infection message is no longer significant.

4.3 Concluding Remarks for Chapter 4

In this chapter, we studied the effectiveness of several mechanisms in the online channel preferences of patients during times of infectious diseases or respiratory virus seasons. Those mechanisms include both direct (price difference and appointment wait time difference) and indirect (messaging) interventions. Table 4.20 provides a summary of the four studies. Study 1 tests the effectiveness of a 25% price difference (a more expensive face-to-face appointment) and a negatively framed infection message that emphasizes the risks for self and others (family members and friends). We observe that the negatively framed infection message is effective in increasing telemedicine adoption during epidemics. Although the price difference instance that we studied has a directional impact on the telemedicine choice, the results are not significant. We believe the insignificant result for the price difference intervention can be due to the need for a larger price difference to have a meaningful impact, or due to the insurance considerations of the participants. As a future direction, varying price differences for the two channels can be studied. Instead of a higher price for the in-person channel, a lower price for the telemedicine channel can be emphasized. Finally, the price difference can be made more salient by showing it in a pop-up screen before the channel choice is made, similar to the case with the nudge messages.

In Study 2, the appointment wait time of the channels is considered, which is known to have a significant impact on patient choice. The provider offers different appointment wait times for the channels as a result of its capacity/resource management policy. The face-to-face option has a 2-week waiting period while the online option has a 1-week waiting period. Once this wait difference is given as is, in the unweighted data, the nudge messages of infection risk and wait time are ineffective in increasing telemedicine channel choice. Study 2 has a biased variable, the wait time risk-taking measure, which hurts the validity of the results. Consequently, Table 4.20 provides the results for the weighted data, which provides partial support for the wait time message. Although we applied two methods to address the problem

Table 4.20: Summary of the studies: date, sample (size), infection risk scenario, results of the hypotheses

	Study 1	Study 2	Study 3	Study 4
Date	Dec, 2023	May, 2024	Nov, 2024	Mar, 2025
Sample (Size)	Students (300)	Students (299)	Students (359)	Prolific (743)
Infection risk scenario	new variant of COVID-19	New virus like Sars-CoV-2	New virus like Sars-CoV-2	CDC seasonal respiratory viruses
IM1	supported			
HP	not supported			
IM2		not supported		
WM		partially supported		
IM3			not supported	
CM1			supported	
IM4				supported
CM2				supported
RISK × IM	not supported	supported (−)	supported (+)	not supported
Travel Time × CM			supported (−)	not supported

with the measure, as a future work, we plan to repeat Study 2 with the corrected measure.

Study 3 approaches the appointment wait time difference from a different perspective. The provider offers similar availability for the two channels. There is potentially a lower appointment wait time for the online channel due to patients' ease of scheduling. Specifically, an online appointment consumes less time in their schedule due to having no travel burden. This may allow an online appointment to be scheduled into a patient's agenda more quickly than a face-to-face appointment, leading to seeing the doctor sooner. We observe that underlining this aspect of the online channel with a positively framed convenience message significantly increases the adoption of the online channel.

Study 4 is conducted to test the hypotheses in the third study within a larger sample with varying ages and educational backgrounds. The fourth study shares the CDC's information on the respiratory virus seasons, instead of sharing a virus scenario. It allows Study 4 to be generalized into settings with no epidemic due to a new virus, as the respiratory virus seasons are repeated during fall, winter, and early spring each year. Supporting the result of Study 3, the convenience message is also effective in Study 4. The potential of the convenience message in increasing the choice for the online channel is promising. The infection risk message has the downside of inducing fear in patients, and it is limited to the epidemic settings. The convenience message, on the other hand, can be used without leading to negative emotions and beyond a virus context.

In conclusion, although it is not possible to compare the effectiveness of nudge messages across the studies, a negatively framed nudge message underlining the self-risks and risks for others has the most impact on increasing online channel adoption during epidemics among the infection messages. We believe this result is highly related to the fact that the first study was closer to the COVID-19 pandemic than the other studies. As we go further away from the pandemic, the effectiveness of the infection message decreases. If both channels have similar availability, underlining the convenience of the online channel by allowing easy scheduling, leading to seeing the doctor sooner, is another effective method in nudging patients toward the online channel. The impact of the convenience message is repeated in two different studies, and the results are robust. That is especially important if the healthcare provider does not want to use infection risk-related messages for patient demand management. For the moderation effects of risk perception and infection message, as well as travel time and convenience message, the results are mixed. Potential factors causing these differences across the studies include the time of the study being close to the COVID-19 pandemic or applied within a respiratory virus season, the participant pool being university students versus Prolific participants from the US with different backgrounds, and the differences in the study design and framing/content of the informational messages. Despite the differences in the results, the use of informational messages in patient demand management is promising. The significance of the infection message in Study 1 shows that the negatively framed infection message can be applied during peak times of an epidemic or a respiratory virus season as an effective tool to increase telemedicine channel choice. The significance of the convenience message, which is supported in two studies with different participant pools, provides an alternative demand management tool that has an impact beyond an epidemic.

Our study has some limitations. First, laboratory experiments may amplify the impact of nudge messages compared to real-world behavior change (Gandhi et al. 2024). This suggests that the actual impact of the informational interventions we study may be lower than what we observe in our experiments. Nevertheless, the consistent results across our experiments strengthen the credibility of our findings. In particular, the convenience message intervention shows a positive effect on increasing telemedicine use across two participant populations with diverse backgrounds. As a direction for future research, the effectiveness of the convenience message could be tested in a laboratory setting without an infection risk. Additionally, testing it in a field experiment would further enhance the external validity of our results. Second, our study does not capture the long-term effectiveness of nudge messages, despite existing evidence that their impact can diminish over time (Sasaki et al. 2021, Çamlıbel et al. 2025). Although the effects of our informational interventions appear short-term, initial exposure to telemedicine can lead to continued use of the channel (González and Scartascini 2024), thereby expanding the patient base for telemedicine services. Overall, the findings of this study offer valuable insights for healthcare providers seeking effective strategies to manage patient demand.

Chapter 5

GENERAL DISCUSSION AND FUTURE PERSPECTIVES

We are in the age of epidemics and expect to see an increase in the frequency of infectious diseases in the future (Roberts 2021, Marani et al. 2021, Gostin 2022). During respiratory virus seasons, the viruses can be detected by routine indoor air screening (Eren et al. 2024). When the hospital environment is risky, providers can apply the interventions we offer in this study to increase the use of telemedicine. That can mitigate potential revenue losses and protect patients and healthcare workers from getting infected. Some of the interventions we offer are more direct, such as capacity allocation and pricing strategies, while the others are indirect and easy to apply (informational interventions). Considering the practicality of the informational interventions, their effectiveness in managing patient channel choice is promising.

Our study supports the United Nations' Sustainable Development Goals (SDGs) of good health and well-being (SDG 3) and decent work (SDG 8) (United Nations 2015). Our study also facilitates building resilient healthcare systems by acknowledging the impact of infection fear on patient channel choice and guiding operational decisions. Advances in technology for remote healthcare delivery (such as wearable devices and other AI-driven technologies) will facilitate the use of the telemedicine channel, underlining the importance of the multichannel healthcare delivery design problem we study.

To the best of our knowledge, our study is the first to define and use contagion awareness of patients in channel decisions. The optimization model embeds all demand fulfillment scenarios and effectively manages patient demand for the channels. It decides whether to open a channel and, given that it is offered, when to close it.

We prove the benefits of telemedicine in mitigating revenue and access losses during epidemics. Our experiments are the first to test the effectiveness of both operational and behavioral mechanisms on patients' channel choices in an epidemic setting. We are the first to study the effectiveness of a convenience message in increasing the use of telemedicine during epidemics. Additionally, our experiment design allows us to show the impact of individual factors (e.g., infection risk perception) on channel preferences.

There are several research directions to be further explored in the design of multichannel healthcare delivery systems. Telemedicine and in-person channels differ in follow-up rates (Gerhart et al. 2022), the number of tests and prescriptions recommended by physicians (Reed et al. 2021), and the completion rates (Haggerty et al. 2022). This highlights the need for comprehensive models that integrate these factors while considering the objectives of different parties: healthcare providers, physicians, insurance companies, and patients. A model that addresses potential incentive misalignments between these parties, for instance, where one party may favor the in-person channel to maximize revenue while another prioritizes telemedicine for its convenience, can be studied. Inspired by the omnichannel retail delivery model of buying online and picking up at a store, one can explore an analogous delivery option in the healthcare domain. The patient encounter between the two channels can be examined, which may involve multiple interactions and cross-channel referrals. For instance, the patient makes the first appointment with telemedicine, the doctor asks for the necessary tests during this virtual appointment, and the patient pays online. Then, she directly visits the hospital for the procedure. Once the results are gathered, another visit can be managed in person or via telemedicine.

In the near future, it is reasonable to anticipate the widespread adoption of AI-supported applications (such as a chatbot asking for medical history and symptoms of a patient to decide the care needed) in patient triage, potentially replacing human decision-making in specific contexts. To ensure the successful integration of such technologies, it is crucial to understand patients' strategic behaviors when interacting with an AI tool compared with a human decision-maker. Wearable devices capable of tracking vital signs like heart rate, blood pressure, and glucose levels in real-time can significantly prevent the progression of health conditions through timely intervention, lowering long-term healthcare costs. One can study the attitudes of patients and healthcare providers toward these devices, which impact the adoption, effectiveness, and overall integration of wearable technology into healthcare systems.

The increasing availability of telehealth platforms offers patients near-instant appointments for various health issues. However, many patients may be unfamiliar with the physicians on these platforms, making physician ratings crucial for reducing uncertainty and building trust. In this context, a field experiment can be designed to explore practical ways to present physician ratings can enhance service quality and increase patient satisfaction.

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Appendix A

PROOF OF LEMMA 1

Let $(\lambda_t, \lambda_i, C_t, C_i, \theta, \alpha, \beta, x_1, y_1, y_2)$ be a feasible solution to the optimization problem (3.1) under which the constraint (3.1g) or (3.1i) is not binding. If (3.1g) is not binding, then decreasing C_t to λ_t neither violates feasibility nor changes the objective function value. Similarly, if (3.1i) is not binding, then decreasing C_i to λ_i neither violates feasibility nor changes the objective function value. Observe that the same logic applies to any objective function that is not a function of C_t or C_i. Consequently, without loss of optimality, we can set $\lambda_t = C_t$ and $\lambda_i = C_i$ also under the following cases:

- The optimization problem (3.1) where the prices are also decision variables (recall Section 5) because the objective function is $p_t\lambda_t + p_i\lambda_i$ which is not a function of C_t or C_i.

- The optimization problem (3.1) under the welfare maximization objective (recall Section 3.4.2). Here, the objective function is $\lambda_t V_t + \lambda_i(V_i - rR(\lambda_i))$ which is not a function of C_t or C_i.

- The optimization problems considered in Section 3.4.3. Here, the revenue and the welfare objectives are

$$p_t\lambda_t + \lambda_i(p_i - d\phi), \qquad V_t\lambda_t + \lambda_i\left(V_i - rR(\lambda_i) - d\phi\right),$$

  respectively, and they are not functions of C_t or C_i.

Next, we will prove the same result for the optimization problem considered in Section 3.4.1. Recall that we update the constraint (3.1j) with the constraint (3.6). Because decreasing C_t to λ_t or C_i to λ_i neither violates the feasibility of the constraints (3.1g), (3.1i), and (3.6) or nor changes the objective function value, without loss of optimality, we can set $\lambda_t = C_t$ and $\lambda_i = C_i$.

Finally, we will prove the same result for the optimization problems considered in Section 3.4.4. The utilities of the telemedicine and in-person channels are

$$U_t' := (1-\tau)(V_t - a_t p_t) + \tau(V_i - a_i p_i - rR(\lambda_i^e) - h) + \epsilon_t,$$
$$U_i' := V_i - a_i p_i - rR(\lambda_i^e) + \epsilon_i,$$

respectively, where $\lambda_i^e := \lambda_i + \tau\lambda_t$ denotes the effective number of in-person appointments. Furthermore, the revenue and the welfare are

$$(1-\tau)p_t\lambda_t + p_i\lambda_i^e,$$
$$\lambda_t((1-\tau)V_t - \tau h) + \lambda_i^e\left(V_i - rR(\lambda_i^e)\right),$$

respectively. Because decreasing C_t to λ_t or C_i to λ_i does not violate the feasibility of the constraints and both the revenue and the welfare objectives are not functions of C_t or C_i, without loss of optimality, we can set $\lambda_t = C_t$ and $\lambda_i = C_i$.

Appendix B

AN AUXILIARY OPTIMIZATION PROBLEM

By Lemma 1, we introduce the following optimization problem which will be useful in the proofs.

$$\max_{\substack{C_t, C_i, \theta, \alpha, \beta, \\ x_1, y_1, y_2}} \quad p_t C_t + p_i C_i \tag{B.1a}$$

$$x_1 + y_1 = 1 - \frac{1}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} \tag{B.1b}$$

$$x_2 = 1 - \frac{1}{1 + e^{V_t - a_t p_t}} \tag{B.1c}$$

$$y_1 = x_1 \frac{e^{V_i - a_i p_i - rR(C_i)}}{e^{V_t - a_t p_t}} \tag{B.1d}$$

$$y_2 = 1 - \frac{1}{1 + e^{V_i - a_i p_i - rR(C_i)}} \tag{B.1e}$$

$$\lambda \left(\theta \left(\alpha x_1 + (1-\alpha)\beta x_2\right) + (1-\theta)\alpha x_1\right) = C_t \tag{B.1f}$$

$$\lambda \left(\theta \alpha y_1 + (1-\theta)\left(\alpha y_1 + (1-\alpha)\beta y_2\right)\right) = C_i \tag{B.1g}$$

$$m_t C_t + m_i C_i \leq C \tag{B.1h}$$

$$C_t + C_i \leq \lambda \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \tag{B.1i}$$

$$C_t, C_i \geq 0 \tag{B.1j}$$

$$x_1, y_1, y_2, \alpha, \beta \in [0, 1] \tag{B.1k}$$

$$\theta \in \{0, 1\} \tag{B.1l}$$

Lemma 2 *The auxiliary optimization problem* (B.1) *is equivalent to the optimization problem* (3.1) *in the sense that they have the same feasible region and optimal objective function value.*

The auxiliary optimization problem (B.1) is obtained by rewriting constraints (3.1b) and (3.1d) of the optimization problem (3.1) where $\lambda_t = C_t$ and $\lambda_i = C_i$ as discussed in the appendix A. We obtain (B.1b) by adding (3.1b) to (3.1d). Once we divide

(3.1d) by (3.1b) and take x_1 to the right-hand side (RHS) of the equation, we obtain (B.1d). Without loss of optimality, we can add (B.1i) to the auxiliary optimization problem (B.1). To see that, let $(C_t, C_i, \theta, \alpha, \beta, x_1, y_1, y_2)$ be a feasible solution to the auxiliary optimization problem (B.1). There are two cases to consider.

Case 1: $\theta = 1$**.** By (B.1c), (B.1f), and (B.1g),

$$\begin{aligned}
&C_i + C_t = \lambda\left(\alpha(x_1+y_1) + (1-\alpha)\beta x_2\right) \leq \lambda\left(\alpha(x_1+y_1)+(1-\alpha)x_2\right)\\
&= \lambda\left(\alpha\frac{e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(C_i)}}{1+e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(C_i)}} + (1-\alpha)\frac{e^{V_t-a_tp_t}}{1+e^{V_t-a_tp_t}}\right)\\
&\leq \lambda\frac{e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(C_i)}}{1+e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(C_i)}} \leq \lambda\frac{e^{V_t}+e^{V_i}}{1+e^{V_t}+e^{V_i}},
\end{aligned}$$

where the last inequality follows from algebra and the fact that $a_ip_i, a_tp_t, rR(C_i) \geq 0$.

Case 2: $\theta = 0$**.** By (B.1e), (B.1f), and (B.1g),

$$\begin{aligned}
&C_i + C_t = \lambda\left(\alpha(x_1+y_1) + (1-\alpha)\beta y_2\right) \leq \lambda\left(\alpha(x_1+y_1)+(1-\alpha)y_2\right)\\
&= \lambda\left(\alpha\frac{e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(C_i)}}{1+e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(C_i)}} + (1-\alpha)\frac{e^{V_i-a_ip_i-rR(C_i)}}{1+e^{V_i-a_ip_i-rR(C_i)}}\right)\\
&\leq \lambda\frac{e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(C_i)}}{1+e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(C_i)}} \leq \lambda\frac{e^{V_t}+e^{V_i}}{1+e^{V_t}+e^{V_i}},
\end{aligned}$$

where the last inequality follows from algebra.

Henceforth, we interchangeably refer to the optimization problem (3.1) and the auxiliary optimization problem (B.1).

Appendix C

PROOF OF THEOREM 1

We start with the proof of part 1.1 of Theorem 1. If $r = 0$ or $R(s) = 0$ and under the condition that all patients are offered both in-person and telemedicine appointments, there exists a trivial feasible solution to the optimization problem (3.1). Because all patients are offered both appointment types, we have Scenario 1 in which $\alpha = 1$. Then, we have $C_t = \lambda x_1$, $C_i = \lambda y_1$, and the objective is $C_t p_t + C_i p_i$. Here, the choice probabilities (x_1, y_1, x_2, y_2) are uniquely determined by the constraints (B.1b)-(B.1e). Because $C = +\infty$, (B.1h) is automatically satisfied. Consequently, offering both appointment types to all patients results in a unique feasible solution to the optimization problem (3.1). Similarly, if only in-person appointments are offered to all patients, we are in Scenario 5.2 and the following feasible solution appears: $\theta = \alpha = C_t = 0$, $\beta = 1$, $C_i = \lambda y_2$, and (x_1, y_1, x_2, y_2) are uniquely determined by the constraints (B.1b)-(B.1e).

Next, we will prove that under the condition (3.2), if $r = 0$ or $R(s) = 0$ for all $s \geq 0$, it is optimal to offer in-person appointments to all patients. That means offering only telemedicine appointments to the patients is suboptimal, and thus, it is optimal to offer either both appointment types or only in-person appointments to all patients. We have

$$\begin{aligned} p_i \frac{e^{V_i - a_i p_i}}{1 + e^{V_i - a_i p_i} + e^{V_t - a_t p_t}} &> p_t \frac{e^{V_i - a_i p_i} e^{V_t - a_t p_t}}{\left(1 + e^{V_t - a_t p_t}\right)\left(1 + e^{V_i - a_i p_i} + e^{V_t - a_t p_t}\right)} \\ &= p_t e^{V_t - a_t p_t} \left(\frac{1}{1 + e^{V_t - a_t p_t}} - \frac{1}{1 + e^{V_i - a_i p_i} + e^{V_t - a_t p_t}} \right), \end{aligned}$$

where the strict inequality follows from (3.2). Therefore,

$$\lambda \left(p_i \frac{e^{V_i - a_i p_i}}{1 + e^{V_i - a_i p_i} + e^{V_t - a_t p_t}} + p_t \frac{e^{V_t - a_t p_t}}{1 + e^{V_i - a_i p_i} + e^{V_t - a_t p_t}} \right) > \lambda p_t \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t}},$$

implying that the revenue from offering both appointment types to all patients is strictly greater than the revenue from offering only telemedicine appointments to all patients. Notice that the RHS of the above inequality represents the revenue when we take $\theta = \beta = 1$ and $\alpha = 0$ according to Scenario 5.1. Consequently, it is suboptimal not to offer in-person appointments to the patients, and by (B.1b), (B.1d), (B.1e), (B.1f), and (B.1g), we have

$$\begin{aligned}\pi^{NR}(\lambda) &= \lambda\left[\left(p_i\frac{\mathrm{e}^{V_i-a_ip_i}}{1+\mathrm{e}^{V_t-a_tp_t}+\mathrm{e}^{V_i-a_ip_i}} + p_t\frac{\mathrm{e}^{V_t-a_tp_t}}{1+\mathrm{e}^{V_t-a_tp_t}+\mathrm{e}^{V_i-a_ip_i}}\right)\vee\left(p_i\frac{\mathrm{e}^{V_i-a_ip_i}}{1+\mathrm{e}^{V_i-a_ip_i}}\right)\right]\\ &\leq \lambda(p_i\vee p_t), \qquad\qquad \text{(C.1)}\end{aligned}$$

where the left-hand-side (LHS) of the inequality above is the maximum of the revenue obtained from offering both channels and the revenue obtained from offering only the in-person channel, and the RHS is a global upper bound. Finally, it is straightforward to see that $C_i(\lambda) = \Theta(\lambda)$ and $\pi^{NR}(\lambda) = \Theta(\lambda)$. If telemedicine appointments are offered to the patients, $C_t(\lambda) = \Theta(\lambda)$; otherwise, $C_t(\lambda) = 0$. Consequently, $C_t(\lambda) = O(\lambda)$, which concludes the proof of part 1.1.

Next, we will prove part 1.2(i) of Theorem 1. First, we show that for a given $\lambda > 0$, a feasible solution to the auxiliary optimization problem (B.1), which is equivalent to the optimization problem (3.1) as stated in Lemma 2, exists. Because both options are offered to all patients, we have $\alpha = 1$ (Scenario 1) in which (B.1f) and (B.1g) simplify into $\lambda x_1 = C_t$ and $\lambda y_1 = C_i$. Consider the constraints (B.1b) and (B.1d). When we write x_1 in terms of y_1 and add them up as in the constraint (B.1b), we have

$$y_1\frac{e^{V_t-a_tp_t}}{e^{V_i-a_ip_i-rR(\lambda y_1)}} + y_1 = 1 - \frac{1}{1+e^{V_t-a_tp_t}+e^{V_i-a_ip_i-rR(\lambda y_1)}}.$$

On the one hand, if $y_1 = 0$, the LHS is zero, which is less than the RHS. On the other hand, if $y_1 = 1$, then LHS is greater than RHS. Because LHS is strictly increasing and RHS is nonincreasing in y_1, there exists a unique y_1 solving the equation. That means there exists a unique y_1 and therefore a unique x_1 satisfying (B.1b) and (B.1d). From (B.1f) and (B.1g), we have $\lambda x_1 = C_t$ and $\lambda y_1 = C_i$. Because $C = \infty$, the constraint (B.1h) is satisfied, and we have Scenario 1 realized, which shows that a unique feasible solution exists under part 1.2(i). Recall that we have $R(s) = b_0 + b_1 s^{b_2}$ where $b_0 \geq 0$ and $b_1, b_2 > 0$. Then, by (B.1d),

$$\begin{aligned}
&\lambda y_1(\lambda) \mathrm{e}^{r\left(b_0 + b_1(\lambda y_1(\lambda))^{b_2}\right)} = \lambda x_1(\lambda) \frac{\mathrm{e}^{V_i - a_i p_i}}{\mathrm{e}^{V_t - a_t p_t}} \implies C_i(\lambda) \mathrm{e}^{r\left(b_0 + b_1(C_i(\lambda))^{b_2}\right)} \\
&= \lambda x_1(\lambda) \frac{\mathrm{e}^{V_i - a_i p_i}}{\mathrm{e}^{V_t - a_t p_t}}, \\
\implies \quad & \ln\left(C_i(\lambda)\right) + r b_0 + r b_1 (C_i(\lambda))^{b_2} = \ln\left(\lambda x_1(\lambda) \frac{\mathrm{e}^{V_i - a_i p_i}}{\mathrm{e}^{V_t - a_t p_t}}\right), \\
\implies \quad & \ln\left(C_i(\lambda)\right) + r b_1 (C_i(\lambda))^{b_2} \leq \ln\left(\lambda \frac{\mathrm{e}^{V_i - a_i p_i}}{\mathrm{e}^{V_t - a_t p_t}}\right) - r b_0. && \text{(C.2)}
\end{aligned}$$

Next, (B.1b) states that

$$\begin{aligned}
&x_1(\lambda) + y_1(\lambda) = 1 - \frac{1}{1 + \mathrm{e}^{V_t - a_t p_t} + \mathrm{e}^{V_i - a_i p_i - r\left(b_0 + b_1(\lambda y_1(\lambda))^{b_2}\right)}}, \\
\implies \quad & y_1(\lambda) \mathrm{e}^{r\left(b_0 + b_1(\lambda y_1(\lambda))^{b_2}\right)} \frac{\mathrm{e}^{V_t - a_t p_t}}{\mathrm{e}^{V_i - a_i p_i}} + y_1(\lambda) = 1 - \frac{1}{1 + \mathrm{e}^{V_t - a_t p_t} + \mathrm{e}^{V_i - a_i p_i - r\left(b_0 + b_1(\lambda y_1(\lambda))^{b_2}\right)}}, \\
\implies \quad & y_1(\lambda) \mathrm{e}^{r\left(b_0 + b_1(\lambda y_1(\lambda))^{b_2}\right)} \frac{\mathrm{e}^{V_t - a_t p_t}}{\mathrm{e}^{V_i - a_i p_i}} + y_1(\lambda) \geq 1 - \frac{1}{1 + \mathrm{e}^{V_t - a_t p_t}}, \\
\implies \quad & C_i(\lambda) \left(1 + \mathrm{e}^{r\left(b_0 + b_1(C_i(\lambda))^{b_2}\right)} \frac{\mathrm{e}^{V_t - a_t p_t}}{\mathrm{e}^{V_i - a_i p_i}}\right) \geq \frac{\mathrm{e}^{V_t - a_t p_t}}{1 + \mathrm{e}^{V_t - a_t p_t}} \lambda. && \text{(C.3)}
\end{aligned}$$

By (C.3), we have $\lim_{\lambda \to \infty} C_i(\lambda) = \infty$. Therefore, there exists a $\lambda_0 \in \mathbb{R}_+$ such that if $\lambda \geq \lambda_0$, then

$$\mathrm{e}^{r\left(b_0 + b_1(C_i(\lambda))^{b_2}\right)} \frac{\mathrm{e}^{V_t - a_t p_t}}{\mathrm{e}^{V_i - a_i p_i}} \geq 1. \tag{C.4}$$

Then, by the inequalities (C.3) and (C.4), if $\lambda \geq \lambda_0$,

$$\begin{aligned}
&2 C_i(\lambda) \mathrm{e}^{r\left(b_0 + b_1(C_i(\lambda))^{b_2}\right)} \frac{\mathrm{e}^{V_t - a_t p_t}}{\mathrm{e}^{V_i - a_i p_i}} \geq \frac{\mathrm{e}^{V_t - a_t p_t}}{1 + \mathrm{e}^{V_t - a_t p_t}} \lambda \\
&\implies C_i(\lambda) \mathrm{e}^{r\left(b_0 + b_1(C_i(\lambda))^{b_2}\right)} \geq \frac{\mathrm{e}^{V_i - a_i p_i}}{2\left(1 + \mathrm{e}^{V_t - a_t p_t}\right)} \lambda, \\
\implies \quad & \ln\left(C_i(\lambda)\right) + r b_1 (C_i(\lambda))^{b_2} \geq \ln\left(\frac{\mathrm{e}^{V_i - a_i p_i}}{2\left(1 + \mathrm{e}^{V_t - a_t p_t}\right)} \lambda\right) - r b_0. && \text{(C.5)}
\end{aligned}$$

Consequently, by (C.2) and (C.5), if $\lambda \geq \lambda_0$,

$$\ln\left(\frac{\mathrm{e}^{V_i - a_i p_i - r b_0}}{2\left(1 + \mathrm{e}^{V_t - a_t p_t}\right)} \lambda\right) \leq \ln\left(C_i(\lambda)\right) + r b_1 (C_i(\lambda))^{b_2} \leq \ln\left(\frac{\mathrm{e}^{V_i - a_i p_i - r b_0}}{\mathrm{e}^{V_t - a_t p_t}} \lambda\right). \tag{C.6}$$

The inequalities in (C.6) imply that there exists a $\lambda_1 \geq \lambda_0$ such that if $\lambda \geq \lambda_1$, then

$$\frac{\ln\left(\hat{a}\lambda\right)}{2 r b_1} \leq (C_i(\lambda))^{b_2} \leq \frac{\ln(\hat{b}\lambda)}{r b_1}, \qquad \text{where} \quad \hat{a} := \frac{\mathrm{e}^{V_i - a_i p_i - r b_0}}{2\left(1 + \mathrm{e}^{V_t - a_t p_t}\right)}, \quad \hat{b} := \frac{\mathrm{e}^{V_i - a_i p_i - r b_0}}{\mathrm{e}^{V_t - a_t p_t}}.$$

(C.7)

Therefore, we have

$$C_i(\lambda) = \Theta((\ln(\lambda))^{1/b_2}).$$

For the telemedicine demand, by (B.1d), we have

$$C_i(\lambda)e^{r\left((b_0+b_1(C_i(\lambda)^{b_2}))\right)} = C_t(\lambda)\frac{e^{V_i-a_ip_i}}{e^{V_t-a_tp_t}}.$$

By (C.6), we know that,

$$\frac{\mathrm{e}^{V_i-a_ip_i-rb_0}}{2\left(1+\mathrm{e}^{V_t-a_tp_t}\right)}\lambda \le C_t(\lambda)\frac{e^{V_i-a_ip_i-rb_0}}{e^{V_t-a_tp_t}} \le \frac{\mathrm{e}^{V_i-a_ip_i-rb_0}}{\mathrm{e}^{V_t-a_tp_t}}\lambda,$$

$$\implies \frac{\lambda}{2\left(1+\mathrm{e}^{V_t-a_tp_t}\right)} \le C_t(\lambda)\frac{1}{e^{V_t-a_tp_t}} \le \frac{\lambda}{e^{V_t-a_tp_t}} \implies C_t(\lambda) = \Theta(\lambda). \qquad \text{(C.8)}$$

Finally, for the revenue, we can write,

$$p_tC_t(\lambda) \le \pi^R(\lambda) = p_iC_i(\lambda) + \lambda p_t\frac{\mathrm{e}^{V_t-a_tp_t}}{1+\mathrm{e}^{V_t-a_tp_t}+\mathrm{e}^{V_i-a_ip_i-r\left(b_0+b_1(C_i(\lambda))^{b_2}\right)}}$$

$$\implies \lambda p_t\frac{e^{V_t-a_tp_t}}{2\left(1+e^{V_t-a_tp_t}\right)} \le \pi^R(\lambda) \le p_iC_i(\lambda) + \lambda p_t\frac{\mathrm{e}^{V_t-a_tp_t}}{1+\mathrm{e}^{V_t-a_tp_t}} \qquad \text{(C.9)}$$

$$\implies \lambda p_t\frac{e^{V_t-a_tp_t}}{2\left(1+e^{V_t-a_tp_t}\right)} \le \pi^R(\lambda) \le \frac{p_i}{(rb_1)^{1/b_2}}(\ln(\hat{b}\lambda))^{1/b_2} + \lambda p_t\frac{\mathrm{e}^{V_t-a_tp_t}}{1+\mathrm{e}^{V_t-a_tp_t}}, \qquad \text{(C.10)}$$

where the inequality in (C.9) follows from (C.8) and the inequality in (C.10) follows from (C.7), and those inequalities hold if $\lambda \ge \lambda_1$. Then, there exists a $\lambda_2 \ge \lambda_1$ such that if $\lambda \ge \lambda_2$, we have

$$\lambda p_t\frac{e^{V_t-a_tp_t}}{2\left(1+e^{V_t-a_tp_t}\right)} \le \pi^R(\lambda) \le 2\lambda p_t\frac{\mathrm{e}^{V_t-a_tp_t}}{1+\mathrm{e}^{V_t-a_tp_t}} \implies \pi^R(\lambda) = \Theta(\lambda),$$

which concludes the proof of Theorem 1 part 1.2(i).

Next, we will prove part 1.2(ii) of Theorem 1. First, we show that for a given $\lambda > 0$, a feasible solution exists. Because only the in-person appointments are offered to all patients, we have $\theta = \alpha = 0$ and $\beta = 1$ (Scenario 5.2) in which (B.1f) and (B.1g) simplify into $C_t = 0$ and $\lambda y_2 = C_i$. By (B.1e),

$$y_2 = 1 - \frac{1}{1+e^{V_i-a_ip_i-rR(\lambda y_2)}}.$$

On the one hand, if $y_2 = 0$, the LHS is zero, which is less than the RHS. On the other hand, if $y_2 = 1$, then LHS is greater than RHS. Because LHS is strictly increasing and RHS is nonincreasing in y_2, there exists a unique y_2 solving the equation. That means there exists a unique $C_i = \lambda y_2$ satisfying the constraint (B.1e). Because $C = \infty$, (B.1h) is satisfied automatically, and we have Scenario 5.2 realized, which shows that a unique feasible solution exists under Theorem 1.2(ii). Finally, since $C_t = 0$, the objective becomes, $\pi^R(\lambda) = p_i C_i(\lambda)$. Recall that $R(s) = b_0 + b_1(s)^{b_2}$. Then,

$$C_i(\lambda) = \lambda \frac{e^{V_i - a_i p_i - r(b_0 + b_1(C_i(\lambda))^{b_2})}}{1 + e^{V_i - a_i p_i - r(b_0 + b_1(C_i(\lambda))^{b_2})}} \geq \lambda \frac{e^{V_i - a_i p_i - r(b_0 + b_1(C_i(\lambda))^{b_2})}}{1 + e^{V_i - a_i p_i}} \tag{C.11}$$

$$\implies \ln(C_i(\lambda)) + r\left(b_0 + b_1(C_i(\lambda))^{b_2}\right) \geq \ln\left(\frac{\lambda e^{V_i - a_i p_i}}{1 + e^{V_i - a_i p_i}}\right).$$

By the equality in (C.11), we also have

$$\begin{aligned}\ln(C_i(\lambda)) + r\left(b_0 + b_1(C_i(\lambda))^{b_2}\right) &= \ln(\lambda) + V_i - a_i p_i - \ln\left(1 + e^{V_i - a_i p_i - r\left(b_0 + b_1(C_i(\lambda))^{b_2}\right)}\right) \\ &\leq \ln(\lambda) + V_i - a_i p_i.\end{aligned}$$

Then, we have

$$\ln\left(\frac{\lambda e^{V_i - a_i p_i - r b_0}}{1 + e^{V_i - a_i p_i}}\right) \leq \ln(C_i(\lambda)) + r\left(b_1(C_i(\lambda))^{b_2}\right) \leq \ln\left(\lambda e^{V_i - a_i p_i - r b_0}\right). \tag{C.12}$$

Recall the definition of $\hat{a}$ in (C.7). By (C.12), there exists a $\lambda_3 \in \mathbb{R}_+$ such that if $\lambda \geq \lambda_3$, we have

$$\frac{\ln(\hat{a}\lambda)}{2rb_1} \leq (C_i(\lambda))^{b_2} \leq \frac{\ln(e^{V_i - a_i p_i - r b_0}\lambda)}{rb_1} \implies C_i(\lambda) = \Theta((\ln(\lambda))^{1/b_2}).$$

Because the revenue is equal to $p_i C_i(\lambda)$, the revenue is also $\Theta((\ln(\lambda))^{1/b_2})$, which concludes the proof of Theorem 1 part 1.2(ii).

Next, we will present the proof of part 1.2(iii). Because only the telemedicine appointments are offered to all patients, we have $\theta = 1$, $\alpha = 0$, and $\beta = 1$. Thus, the constraints (B.1f) and (B.1g) simplify into $C_i = 0$ and $C_t = \lambda x_2$, where x_2 is given in (B.1c). Because $C = \infty$, (B.1h) is satisfied automatically, and we have Scenario 5.1 realized, which shows that a feasible solution exists under Theorem 1 part 1.2(iii).

Finally, since $C_i = 0$, the objective function becomes equal to $\pi^R(\lambda) = p_t C_t(\lambda)$ where

$$C_t(\lambda) = \lambda \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t}}.$$

Then, we have $C_t(\lambda) = \Theta(\lambda)$ and $\pi^R(\lambda) = \Theta(\lambda)$.

Finally, we will compute the revenue loss due to the effect of contagion for part 1.2(i). Because the proofs for the cases 1.2(ii) and 1.2(iii) are very similar to the proof of the case 1.2(i), we skip them. First, by (C.1),

$$\pi^{NR}(\lambda) - \pi^R(\lambda) \leq \pi^{NR}(\lambda) \leq \lambda(p_i \vee p_t). \tag{C.13}$$

Second, by (C.1) and (C.10), if $\lambda \geq \lambda_1$,

$$\pi^{NR}(\lambda) - \pi^R(\lambda) \geq \lambda \frac{\mathrm{e}^{V_i - a_i p_i}}{1 + \mathrm{e}^{V_t - a_t p_t} + \mathrm{e}^{V_i - a_i p_i}} \left(p_i - p_t \frac{\mathrm{e}^{V_t - a_t p_t}}{1 + \mathrm{e}^{V_t - a_t p_t}} \right) - \frac{p_i}{(r b_1)^{1/b_2}} (\ln(\hat{b}\lambda))^{1/b_2}. \tag{C.14}$$

By (3.2) and (C.14), there exists a $\lambda_4 \geq \lambda_1$ such that if $\lambda \geq \lambda_4$, then

$$\pi^{NR}(\lambda) - \pi^R(\lambda) \geq 0.5\lambda \frac{\mathrm{e}^{V_i - a_i p_i}}{1 + \mathrm{e}^{V_t - a_t p_t} + \mathrm{e}^{V_i - a_i p_i}} \left(p_i - p_t \frac{\mathrm{e}^{V_t - a_t p_t}}{1 + \mathrm{e}^{V_t - a_t p_t}} \right). \tag{C.15}$$

Condition (3.2) and the inequalities in (C.13) and (C.15) imply that $\pi^{NR}(\lambda) - \pi^R(\lambda) = \Theta(\lambda)$.

Appendix D

PROOF OF THEOREM 2

In this proof, we consider the optimization problem (3.1) (or equivalently the auxiliary optimization problem (B.1)) where the pair (p_t, p_i) is a nonnegative decision variable. First, we prove that under the pricing optimization, any feasible solution in which $\alpha \in (0, 1)$ is suboptimal. Next, we show that at $\alpha = 0$ or $\alpha = 1$, the pricing optimization problem simplifies into (3.3). Finally, we prove that (3.3) always has an optimal solution and is a convex optimization problem under a polynomial contagion effect.

Lemma 3 *Under pricing optimization, a feasible solution under which* $\alpha \in (0, 1)$ *is suboptimal. Therefore, an optimal solution is attained only when* $\alpha \in \{0, 1\}$.

Suppose that $(C_t, C_i, \theta, \alpha, \beta, x_1, y_1, y_2, p_i, p_t)$ is a feasible solution of the auxiliary optimization problem (B.1) in which $\alpha \in (0, 1)$. We will construct a new feasible solution with a strictly greater objective function value, implying that the former feasible solution is suboptimal. There are three cases to consider. Before starting the cases, observe that for $\alpha > 0$, $C_t \wedge C_i > 0$ as $x_1, x_2, y_1, y_2 > 0$ by (3.1b), (3.1c), (3.1d), and (3.1e).

Case 1. $\theta = 1$ ***and*** $\beta \in (0, 1]$***.*** By (B.1f) and (B.1g), we have $\alpha x_1 + (1-\alpha)\beta x_2 = C_t/\lambda$ and $\alpha y_1 = C_i/\lambda$. And, the objective function value of this feasible solution is $p_i C_i + p_t C_t$. Now, we will construct another feasible solution by increasing the in-person price p_i while keeping (C_i, C_t) fixed. We will denote this new feasible solution by $(C_t, C_i, \theta, \alpha', \beta', x_1', y_1', y_2', p_i', p_t)$, where $p_i' = p_i + \epsilon$ such that $\epsilon > 0$ is sufficiently small. We use the superscript $'$ to denote the decision variables that are different than the ones in the former feasible solution. First, we will show that if $\epsilon > 0$ is small enough, then, there exists an $\alpha' \leq 1$ under which $\alpha' y_1' = C_i/\lambda$. When we increase p_i by ϵ, by (3.1d),

$$y_1' = \frac{e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}.$$

Then, we have

$$\alpha' = \frac{C_i}{\lambda y_1'} = \frac{C_i}{\lambda}\frac{1 + e^{V_t - a_t p_t} + e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}{e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}} = \alpha y_1 \frac{1 + e^{V_t - a_t p_t} + e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}{e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}. \tag{D.1}$$

By (3.1d),

$$y_1 = \frac{e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} \implies \alpha' = \alpha e^{a_i \epsilon}\frac{1 + e^{V_t - a_t p_t} + e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}}.$$

We have as $\epsilon \to 0$, $\alpha' \to \alpha$. By the continuity of α' in ϵ, and because $\alpha \in (0,1)$, if $\epsilon > 0$ is sufficiently small, then, $\alpha' \leq 1$. We can write the expression for α' in terms of α, ϵ and y_1 as such,

$$\begin{aligned}\alpha' &= \alpha e^{a_i\epsilon}\left(\frac{1}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} + x_1 + \frac{y_1}{e^{a_i\epsilon}}\right) = \alpha e^{a_i\epsilon}\left(1 - y_1 + \frac{y_1}{e^{a_i\epsilon}}\right)\\ &= \alpha\left(e^{a_i\epsilon}(1-y_1) + y_1\right),\end{aligned} \tag{D.2}$$

where the second equality follows from (B.1b). Next, we will show the existence of β' which satisfies the equality (B.1f). To do that, we will look at the difference between $\alpha x_1 + (1-\alpha)x_2$ and $\alpha' x_1' + (1-\alpha')x_2$. We have the following equality from (3.1b) and (D.1).

$$\begin{aligned}\alpha' x_1' &= \frac{C_i}{\lambda}\frac{1 + e^{V_t - a_t p_t} + e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}{e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}\frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}}\\ &= \frac{C_i}{\lambda}\frac{e^{V_t - a_t p_t}}{e^{V_i - a_i(p_i+\epsilon) - rR(C_i)}} = \alpha x_1 e^{a_i\epsilon},\end{aligned} \tag{D.3}$$

where the last equality follows from (3.1b), (3.1d), and (D.1) since

$$\alpha x_1 = \frac{C_i}{\lambda y_1}x_1 = \frac{C_i}{\lambda}\frac{e^{V_t - a_t p_t}}{e^{V_i - a_i p_i - rR(C_i)}}$$

where the second equality follows from (3.1b) and (3.1d). Then, we have

$$
\begin{aligned}
&\alpha x_1 + (1-\alpha)x_2 - \alpha' x_1' - (1-\alpha')x_2 \\
&= \alpha x_1 \left(1 - e^{a_i \epsilon}\right) + x_2(\alpha' - \alpha) \\
&= \alpha x_1 \left(1 - e^{a_i \epsilon}\right) + \alpha x_2 \left(e^{a_i \epsilon} - e^{a_i \epsilon} y_1 + y_1 - 1\right) \\
&= \alpha x_1 \left(1 - e^{a_i \epsilon}\right) + \alpha x_2 (1 - y_1)\left(e^{a_i \epsilon} - 1\right) \\
&= \alpha \left(1 - e^{a_i \epsilon}\right)\left(x_1 - x_2(1 - y_1)\right) \\
&= \alpha \left(1 - e^{a_i \epsilon}\right)\big(\frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} \\
&- \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t}}\big(1 - \frac{e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}}\big)\big) = 0, \qquad \text{(D.4)}
\end{aligned}
$$

where the first equality follows from (D.3) and the second equality follows from (D.2). By (D.4), we have

$$
\alpha' x_1' - \alpha x_1 = (1-\alpha)x_2 - (1-\alpha')x_2 = (\alpha' - \alpha)x_2 > 0
$$

where the strict equality follows from (D.2). Then, we need $\beta' < \beta$ for (B.1f) to hold. By (B.1f),

$$
\beta' = \frac{\frac{C_t}{\lambda} - \alpha' x_1'}{(1-\alpha')x_2} = \frac{\alpha x_1 + (1-\alpha)\beta x_2 - \alpha x_1 e^{a_i \epsilon}}{\left(1 - \alpha\left(e^{a_i \epsilon}(1 - y_1) + y_1\right)\right)x_2},
$$

where the second equality follows from (D.2) and (D.3). Observe that β' is continuous and decreasing in ϵ when ϵ is sufficiently small. In other words, as ϵ decreases to 0, β' approaches β from below. Because β' approaches β from below as ϵ decreases to 0 and $\beta > 0$, there exists an $\epsilon > 0$ sufficiently small at which $\beta' \geq 0$ and (B.1f) is satisfied. The objective function value of this new solution is $p_i' C_i + p_t C_t = (p_i + \epsilon)C_i + p_t C_t$. Consequently, increasing in-person price by $\epsilon > 0$ small enough, increases the revenue by ϵC_i.

Case 2. $\theta = 0$ ***and*** $\beta \in (0, 1]$**.** By (B.1f) and (B.1g), we have $\alpha x_1 = C_t/\lambda$ and $\alpha y_1 + (1-\alpha)\beta y_2 = C_i/\lambda$. And, the objective function value of this feasible solution is $p_i C_i + p_t C_t$. Now, we will construct another feasible solution by increasing the telemedicine price p_t while keeping (C_i, C_t) fixed. We will denote this new solution by $(C_t, C_i, \theta, x_1', y_1', y_2, \alpha', \beta', p_i, p_t')$, where $p_t' = p_t + \epsilon$ such that $\epsilon > 0$ is sufficiently small. First, we will show that if $\epsilon > 0$ is small enough, then, there exists an $\alpha' \leq 1$ under which $\alpha' x_1' = C_t/\lambda$. When we increase p_t by ϵ, by (3.1b),

$$x_1' = \frac{e^{V_t - a_t(p_t+\epsilon)}}{1 + e^{V_t - a_t(p_t+\epsilon)} + e^{V_i - a_i p_i - rR(C_i)}}.$$

Then, we have

$$\alpha' = \frac{C_t}{\lambda x_1'} = \frac{C_t}{\lambda} \frac{1 + e^{V_t - a_t(p_t+\epsilon)} + e^{V_i - a_i p_i - rR(C_i)}}{e^{V_t - a_t(p_t+\epsilon)}} = \alpha x_1 \frac{1 + e^{V_t - a_t(p_t+\epsilon)} + e^{V_i - a_i p_i - rR(C_i)}}{e^{V_t - a_t(p_t+\epsilon)}}. \tag{D.5}$$

By (3.1b),

$$x_1 = \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} \implies \alpha' = \alpha e^{a_t \epsilon} \frac{1 + e^{V_t - a_t(p_t+\epsilon)} + e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}}.$$

We have as $\epsilon \to 0$, $\alpha' \to \alpha$. By the continuity of α' in ϵ, and because $\alpha \in (0, 1)$, if $\epsilon > 0$ is sufficiently small, then $\alpha' \leq 1$. We can write the expression for α' in terms of α, ϵ, and x_1 as such

$$\begin{aligned} \alpha' &= \alpha e^{a_t \epsilon} \left(\frac{1}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} + \frac{x_1}{e^{a_t \epsilon}} + y_1 \right) = \alpha e^{a_t \epsilon} \left(1 - x_1 + \frac{x_1}{e^{a_t \epsilon}} \right) \\ &= \alpha \left(e^{a_t \epsilon}(1 - x_1) + x_1 \right), \end{aligned} \tag{D.6}$$

where the second equality follows from (B.1b). Next, we will show the existence of β' which satisfies the equality (B.1g). To do that, we will look at the difference between $\alpha y_1 + (1-\alpha) y_2$ and $\alpha' y_1' + (1-\alpha') y_2$. We have the following equality from (D.5) and (3.1b).

$$\begin{aligned} \alpha' y_1' &= \frac{C_t}{\lambda} \frac{1 + e^{V_t - a_t(p_t+\epsilon)} + e^{V_i - a_i p_i - rR(C_i)}}{e^{V_t - a_t(p_t+\epsilon)}} \frac{e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_t - a_t(p_t+\epsilon)} + e^{V_i - a_i p_i - rR(C_i)}} \\ &= \frac{C_t}{\lambda} \frac{e^{V_i - a_i p_i - rR(C_i)}}{e^{V_t - a_t(p_t+\epsilon)}} = \alpha y_1 e^{a_t \epsilon} \end{aligned} \tag{D.7}$$

where the last equality follows from (3.1b), (3.1d), and (D.5) since

$$\alpha y_1 = \frac{C_t}{\lambda x_1} y_1 = \frac{C_t}{\lambda} \frac{e^{V_i - a_i p_i - rR(C_i)}}{e^{V_t - a_t p_t}}$$

where the second equality follows from (3.1b) and (3.1d). Then, we have

$$\begin{aligned}
&\alpha y_1 + (1-\alpha)y_2 - \alpha' y_1' - (1-\alpha')y_2 \\
&= \alpha y_1 \left(1 - e^{a_t \epsilon}\right) + y_2(\alpha' - \alpha) \\
&= \alpha y_1 \left(1 - e^{a_t \epsilon}\right) + \alpha y_2 \left(e^{a_t \epsilon} - e^{a_t \epsilon} x_1 + x_1 - 1\right) \\
&= \alpha y_1 \left(1 - e^{a_t \epsilon}\right) + \alpha y_2 (1 - x_1) \left(e^{a_t \epsilon} - 1\right) \\
&= \alpha \left(1 - e^{a_t \epsilon}\right) \left(y_1 - y_2(1 - x_1)\right) \\
&= \alpha \left(1 - e^{a_t \epsilon}\right) \Big(\frac{e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} \\
&- \frac{e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_i - a_i p_i - rR(C_i)}} \left(\frac{1 + e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} \right) \Big) = 0, \qquad \text{(D.8)}
\end{aligned}$$

where the first equality follows from (D.7) and the second equality follows from (D.6). By (D.8), we have

$$\alpha' y_1' - \alpha y_1 = (1-\alpha)y_2 - (1-\alpha')y_2 = (\alpha - \alpha')y_2 > 0,$$

where the strict equality follows from (D.6). Then, we need $\beta' < \beta$ for (B.1g) to hold. By (B.1g),

$$\beta' = \frac{\frac{C_i}{\lambda} - \alpha' y_1'}{(1-\alpha')y_2} = \frac{\alpha y_1 + (1-\alpha)\beta y_2 - \alpha y_1 e^{a_t \epsilon}}{\left(1 - \alpha \left(e^{a_t \epsilon}(1 - x_1) + x_1\right)\right) y_2},$$

where the second equality follows from (D.6) and (D.7). Observe that β' is continuous and decreasing in ϵ when ϵ is sufficiently small. In other words, as ϵ decreases to 0, β' approaches β from below. Because β' approaches β from below as ϵ decreases to 0 and $\beta > 0$, there exists an $\epsilon > 0$ sufficiently small at which $\beta' \geq 0$ and (B.1g) is satisfied. The objective function value of this new solution is $p_i C_i + p_t' C_t = p_i C_i + (p_t + \epsilon) C_t$. Consequently, increasing telemedicine price by a sufficiently small $\epsilon > 0$ increases the revenue by ϵC_t.

Case 3. $\beta = 0$**.** Note that the value of θ does not make a difference in this case because (B.1f) and (B.1g) are the same under $\theta = 1$ and $\theta = 0$. By (3.1b) and (3.1d), we have

$$x_1 = \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}}, \quad y_1 = \frac{e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}}$$

where the objective function value is $z = p_t C_t + p_i C_i$. We will construct a new feasible solution $(C_t, C_i, \theta, x_1', y_1', y_2', \alpha', \beta, p_i', p_t')$ such that $p_t' = p_t + \epsilon_t$, $p_i' = p_i + \epsilon_i$, $\epsilon_t \wedge \epsilon_i > 0$, $x_1' < x_1$, $y_1' < y_1$, $\alpha' > \alpha$. We keep C_t, C_i, θ, β as before. The new objective function value is $z' = p_t' C_t + p_i' C_i$ and $z' - z = \epsilon_t C_t + \epsilon_i C_i > 0$. By (3.1b) and (3.1d),

$$x_1' = \frac{e^{V_t - a_t(p_t+\epsilon_t)}}{1 + e^{V_t - a_t(p_t+\epsilon_t)} + e^{V_i - a_i(p_i+\epsilon_i) - rR(C_i)}}, \quad y_1' = \frac{e^{V_i - a_i(p_i+\epsilon_i) - rR(C_i)}}{1 + e^{V_t - a_t(p_t+\epsilon_t)} + e^{V_i - a_i(p_i+\epsilon_i) - rR(C_i)}}.$$

Then we can write,

$$\begin{aligned}
\frac{x_1}{x_1'} &= e^{a_t\epsilon_t} \frac{1 + e^{V_t - a_t(p_t+\epsilon_t)} + e^{V_i - a_i(p_i+\epsilon_i) - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}}, \\
\frac{y_1}{y_1'} &= e^{a_i\epsilon_i} \frac{1 + e^{V_t - a_t(p_t+\epsilon_t)} + e^{V_i - a_i(p_i+\epsilon_i) - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}}.
\end{aligned}$$

Because $\epsilon_t \wedge \epsilon_i > 0$ and $a_t, a_i > 0$, we have the first components in the above multiplications greater than 1 and the second components, which are the same for the two equalities, less than 1. Next, we will choose ϵ_t and ϵ_i in a way that $x_1/x_1' = y_1/y_1'$. For that we need

$$e^{a_t\epsilon_t} = e^{a_i\epsilon_i} \quad \Longrightarrow a_i\epsilon_i = a_t\epsilon_t \quad \Longrightarrow \epsilon_i = \frac{1}{a_i} a_t \epsilon_t. \tag{D.9}$$

For any $\epsilon_t > 0$, ϵ_i as a function of ϵ_t, which we write $\epsilon_i(\epsilon_t)$, defined in (D.9) is well-defined and $\epsilon_i(\epsilon_t) > 0$ because $a_t, a_i > 0$. Moreover, $\epsilon_i(\cdot)$ defined in (D.9) is continuous in ϵ_t. Consequently, under $\epsilon_i(\epsilon_t)$ defined in (D.9), $x_1/x_1' = y_1/y_1'$ for all $\epsilon_t > 0$. Next, we will prove that $x_1/x_1' = y_1/y_1' > 1$ for all $\epsilon_t > 0$ under (D.9). Let

$$a := e^{V_t - a_t p_t}, \quad \tilde{a} := e^{V_t - a_t(p_t+\epsilon_t)}, \quad b := e^{V_i - a_i p_i - rR(C_i)}, \quad \tilde{b} := e^{V_i - a_i(p_i+\epsilon_i) - rR(C_i)}.$$

Then, by (D.9), we have

$$\frac{a}{\tilde{a}} = \frac{b}{\tilde{b}} = e^{a_t\epsilon_t} = e^{a_i\epsilon_i} > 1.$$

We also have

$$\frac{x_1}{x_1'} = \frac{a}{\tilde{a}} \cdot \frac{1 + \tilde{a} + \tilde{b}}{1 + a + b} = \frac{\frac{\tilde{a}}{a} + a + \frac{a}{\tilde{a}}\tilde{b}}{1 + a + b} = \frac{\frac{\tilde{a}}{a} + a + \frac{b}{\tilde{b}}\tilde{b}}{1 + a + b} = \frac{\frac{a}{\tilde{a}} + a + b}{1 + a + b} > 1. \tag{D.10}$$

Fix an arbitrary $\epsilon_t > 0$ and let $\epsilon_i(\epsilon_t)$ be defined as in (D.9). Next, we will specify α'. By (B.1f) and (B.1g), we have $\lambda\alpha' x_1' = C_t = \lambda\alpha x_1$ and $\lambda\alpha' y_1' = C_i = \lambda\alpha y_1$. By (D.10), we have

$$\alpha' := \alpha\frac{x_1}{x_1'} = \alpha\frac{y_1}{y_1'} > \alpha. \tag{D.11}$$

By (D.10) and (D.11), α' is continuous in ϵ_t and as $\epsilon_t \downarrow 0$, $\alpha'(\epsilon_t) \downarrow \alpha$. Because $\alpha < 1$, there exists an $\epsilon_t > 0$ sufficiently small such that $\alpha < \alpha'(\epsilon_t) \leq 1$. Then, if $\epsilon_t > 0$ is sufficiently small and under (D.9) and (D.11), $(C_t, C_i, \theta, x_1', y_1', y_2', \alpha', \beta, p_i', p_t')$ becomes a feasible solution of the optimization problem (3.1) with $z' - z = \epsilon_t C_t + \epsilon_i C_i > 0$.

Lemma 4 *Under pricing optimization, the optimization problem* (3.1) *simplifies into* (3.3).

By Lemma 3, a feasible solution to the optimization problem (3.1) in which $\alpha \in (0,1)$ is suboptimal. Therefore, under an optimal solution to the optimization problem (3.1), we must have $\alpha \in \{0,1\}$. First, in Case 1, we fix $\alpha = 1$ where the value of β is not of concern due to the term $(1-\alpha)\beta$. Then, (B.1f) and (B.1g) simplify into $\lambda x_1 = C_t$ and $\lambda y_1 = C_i$ independent of the value of β and θ. Furthermore, $(x_1, y_1, y_2, p_t, p_i)$ are uniquely determined by a given (C_t, C_i) such that the solution $(x_1, y_1, y_2, p_t, p_i)$ satisfies the corresponding constraints. In Cases 2 and 3, we fix $\alpha = 0$ and follow a similar logic. Combining the resulting optimization problems in the following three cases under the assumption $0\times\infty = 0$, we obtain the optimization problem (3.3).

Case 1. $\alpha = 1$**.** By (3.1b) and (3.1d), we have

$$x_1 = \frac{e^{V_t - a_t p_t}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} = \frac{C_t}{\lambda}, \quad y_1 = \frac{e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_t - a_t p_t} + e^{V_i - a_i p_i - rR(C_i)}} = \frac{C_i}{\lambda}.$$

Taking the ratio,

$$\begin{aligned}
&\frac{y_1}{x_1} = \frac{e^{V_i - a_i p_i - rR(C_i)}}{e^{V_t - a_t p_t}} = \frac{C_i}{C_t} \\
&\Longrightarrow V_i - a_i p_i - rR(C_i) - V_t + a_t p_t = \ln(C_i) - \ln(C_t), \\
&\Longrightarrow a_i p_i = a_t p_t + V_i - rR(C_i) - V_t - \ln(C_i) + \ln(C_t).
\end{aligned}$$

By plugging the expression for a_ip_i above into the definition of x_1, we obtain

$$
\begin{aligned}
x_1 &= \frac{e^{V_t - a_tp_t}}{1 + e^{V_t - a_tp_t} + e^{V_t - a_tp_t - \ln(C_t) + \ln(C_i)}} = \frac{C_t}{\lambda} \\
\implies \lambda e^{V_t - a_tp_t} &= C_t + C_t e^{V_t - a_tp_t} + C_t e^{V_t - a_tp_t} e^{\ln(C_i) - \ln(C_t)}, \\
\implies e^{V_t - a_tp_t}(\lambda - C_t - C_t e^{\ln(C_i) - \ln(C_t)}) &= C_t \implies e^{V_t - a_tp_t}(\lambda - C_t - C_i) = C_t, \\
\implies p_t &= \frac{1}{a_t}\left(V_t - \ln(C_t) + \ln(\lambda - C_t - C_i)\right).
\end{aligned}
$$

By plugging $a_tp_t = V_t - \ln(C_t) + \ln(\lambda - C_t - C_i)$ into the equation $a_ip_i = a_tp_t + V_i - rR(C_i) - V_t - \ln(C_i) + \ln(C_t)$, we obtain,

$$
p_i = \frac{1}{a_i}(V_i - rR(C_i) - \ln(C_i) + \ln(\lambda - C_t - C_i)).
$$

Therefore when $\alpha = 1$, there is a one-to-one relationship between (C_t, C_i) and (p_t, p_i) and it is enough to choose only (C_t, C_i) optimally. Therefore, the optimization problem (3.1) simplifies into (3.3) where the objective function is,

$$
C_t \frac{1}{a_t}(V_t - \ln(C_t) + \ln(\lambda - C_t - C_i)) + C_i \frac{1}{a_i}(V_i - rR(C_i) - \ln(C_i) + \ln(\lambda - C_t - C_i)),
$$

and the constraints (3.3b), (3.3c), and (3.3d) directly follow from (B.1h), (B.1i), and (B.1j), respectively.

Case 2. ***$\alpha = 0$ and $\theta = 1$.*** Here, $C_i = 0$ and the provider only offers telemedicine appointments. In that case, we have $\lambda\beta x_2 = C_t$ where the revenue is p_tC_t. Similar to what we did in the proof of Lemma 3, keeping C_t fixed, increasing p_t by $\epsilon > 0$ sufficiently small, increases the revenue by ϵC_t. By (3.1d), x_2 decreases with an increase in p_t and to keep $\lambda\beta x_2 = C_t$ feasible, we need to increase β. Consequently, one can increase the revenue by increasing p_t until $\beta = 1$. Then, we have

$$
\begin{aligned}
& \lambda x_2 = \lambda \frac{e^{V_t - a_tp_t}}{1 + e^{V_t - a_tp_t}} = C_t \implies \lambda e^{V_t - a_tp_t} = C_t + C_t e^{V_t - a_tp_t}, \\
\implies \quad & (\lambda - C_t) e^{V_t - a_tp_t} = C_t \implies V_t - a_tp_t = \ln(C_t) - \ln(\lambda - C_t), \\
\implies \quad & a_tp_t = V_t - \ln(C_t) + \ln(\lambda - C_t) \implies p_t = \frac{1}{a_t}(V_t - \ln(C_t) + \ln(\lambda - C_t)).
\end{aligned}
$$

Consequently, the optimization problem (3.1) simplifies into (3.3).

Case 3. $\alpha = 0$ ***and*** $\theta = 0$**.** Here, $C_t = 0$ and the provider only offers in-person appointments. In that case, we have $\lambda\beta y_2 = C_i$, and similar to Case 2, one can increase the revenue by increasing p_i until β hits 1. Therefore, without loss of optimality, we let $\beta = 1$. Then, we have

$$\begin{aligned}
&\lambda y_2 = \lambda \frac{e^{V_i - a_i p_i - rR(C_i)}}{1 + e^{V_i - a_i p_i - rR(C_i)}} = C_i \\
&\Longrightarrow \lambda e^{V_i - a_i p_i - rR(C_i)} = C_i + C_i e^{V_i - a_i p_i - rR(C_i)}, \\
&\Longrightarrow (\lambda - C_i) e^{V_i - a_i p_i - rR(C_i)} = C_i \implies V_i - a_i p_i - rR(C_i) = \ln(C_i) - \ln(\lambda - C_i), \\
&\Longrightarrow p_i = \frac{1}{a_i}(V_i - rR(C_i) - \ln(C_i) + \ln(\lambda - C_i)).
\end{aligned}$$

Consequently, the optimization problem (3.1) simplifies into (3.3).

Next, we argue that (3.3) always has an optimal solution. First, observe that the feasible region defined in (3.3b) - (3.3d) is a closed and compact subset of $\mathbb{R}^2$. Second, if $C_t \wedge C_i > 0$, then the objective function is well-defined and continuous in (C_t, C_i) in the feasible region. Because

$$\lim_{C_t \downarrow 0} \frac{C_t}{a_t}(V_t - \ln(C_t) + \ln(\lambda - C_t - C_i)) = 0, \quad \lim_{C_i \downarrow 0} \frac{C_i}{a_i}(V_i - rR(C_i) - \ln(C_i) + \ln(\lambda - C_t - C_i)) = 0,$$

and we assume $0 \times \infty = 0$, the objective function is continuous even when $C_t \wedge C_i = 0$. Consequently, the objective function is well-defined and continuous in the entire feasible region. Consequently, by the extreme value theorem, the objective function attains its maximum, and thus an optimal solution exists.

Finally, we show that (3.3) is a convex optimization problem under the polynomial contagion effect $R(s) = b_0 + b_1 s^{b_2}$ where $b_0 \geq 0$ and $b_1, b_2 > 0$. Let H denote the Hessian of the objective function. Then,

$$H = \begin{bmatrix} -\frac{1}{a_i a_t}\left(\frac{a_t C_i C_t + a_i(\lambda - C_i)^2}{C_t(\lambda - C_t - C_i)^2}\right) & -\frac{1}{a_i a_t}\left(\frac{\lambda(a_i + a_t) - a_t C_t - a_i C_i}{(\lambda - C_t - C_i)^2}\right) \\ -\frac{1}{a_i a_t}\left(\frac{\lambda(a_i + a_t) - a_t C_t - a_i C_i}{(\lambda - C_t - C_i)^2}\right) & -\frac{1}{a_i a_t}\left(\frac{a_t}{C_i} + a_t r b_1 b_2 C_i^{b_2 - 1}(1 + b_2) + \frac{2\lambda a_t + (a_i - 2a_t)C_t - a_t C_i}{(\lambda - C_t - C_i)^2}\right) \end{bmatrix}.$$

Let us fix an arbitrary feasible (C_t, C_i) pair. Let the superscript T denote the transpose sign. Then, the objective function is strictly concave if and only if $z^T H z <$

0 for all $z = (z_1; z_2) \in \mathbb{R}^2 \setminus \{(0;0)\}$. By algebra, for all $z \in \mathbb{R}^2 \setminus \{(0;0)\}$, we have

$$\begin{aligned}
z^T H z &= -\frac{1}{a_i a_t}\left(z_1^2 \frac{a_t C_i}{(\lambda - C_t - C_i)^2} + z_2^2 \frac{a_i C_t}{(\lambda - C_t - C_i)^2} + 2 z_1 z_2 \left(\frac{a_i(\lambda - C_i) + a_t(\lambda - C_t)}{(\lambda - C_t - C_i)^2}\right)\right. \\
&\qquad \left. + z_1^2 \frac{a_i(\lambda - C_i)^2}{C_t(\lambda - C_t - C_i)^2} + z_2^2 \left(\frac{a_t(\lambda - C_t)^2}{C_i(\lambda - C_t - C_i)^2} + a_t r b_1 b_2 C_i^{b_2 - 1}(1 + b_2)\right)\right) \\
&= -\frac{1}{a_i a_t}\left(\frac{a_i\left((\lambda - C_i) z_1 + C_t z_2\right)^2}{C_t(\lambda - C_t - C_i)^2} + \frac{a_t\left(z_1 C_i + (\lambda - C_t) z_2\right)^2}{C_i(\lambda - C_t - C_i)^2} + z_2^2 a_t r b_1 b_2 C_i^{b_2 - 1}(1 + b_2)\right) \\
&< 0
\end{aligned}$$

by (3.3c) and (3.3d). Therefore, the objective function is strictly concave. Consequently, (3.3) is a convex optimization problem.

Appendix E

PROOF OF THEOREM 3

We will solve the first-order conditions (FOCs) to find the unique maximizer of the objective function. The two FOCs are as follows.

$$-\ln(C_t) + V_t - 1 + \ln(\lambda - C_t - C_i) - \frac{C_t + C_i}{\lambda - C_t - C_i} = 0, \tag{E.1a}$$

$$-\ln(C_i) + V_i - 1 + \ln(\lambda - C_t - C_i) - \frac{C_t + C_i}{\lambda - C_t - C_i} - r\left(b_0 + b_1 (C_i)^{b_2}(1 + b_2)\right) = 0. \tag{E.1b}$$

We will prove that under the conditions stated in the theorem statement, the unique maximizer of the objective function, which solves (E.1a) and (E.1b), satisfies (3.3b), (3.3c), and (3.3d), and thus it is feasible and optimal. First, (E.1a) leads to

$$\ln\left(\frac{\lambda - C_t - C_i}{C_t}\right) = \frac{C_t + C_i}{\lambda - C_t - C_i} + 1 - V_t \implies \lambda - C_t - C_i = C_t e^{\frac{C_t + C_i}{\lambda - C_t - C_i} + 1 - V_t}. \tag{E.2}$$

Second, (E.1b) leads to

$$\ln\left(\frac{\lambda - C_t - C_i}{C_i}\right) = \frac{C_t + C_i}{\lambda - C_t - C_i} + 1 - V_i + r\left(b_0 + b_1 (C_i)^{b_2}(1 + b_2)\right),$$
$$\implies \lambda - C_t - C_i = C_i e^{\frac{C_t + C_i}{\lambda - C_t - C_i} + 1 - V_i + r\left(b_0 + b_1 (C_i)^{b_2}(1 + b_2)\right)}. \tag{E.3}$$

By (E.2) and (E.3), we have

$$C_t e^{\frac{C_t + C_i}{\lambda - C_t - C_i} + 1 - V_t} = C_i e^{\frac{C_t + C_i}{\lambda - C_t - C_i} + 1 - V_i + r\left(b_0 + b_1 (C_i)^{b_2}(1 + b_2)\right)} \implies C_t = C_i e^{V_t - V_i + r\left(b_0 + b_1 (C_i)^{b_2}(1 + b_2)\right)}. \tag{E.4}$$

By (E.2),

$$C_t\left(1 + e^{\frac{C_t + C_i}{\lambda - C_t - C_i} + 1 - V_t}\right) + C_i = \lambda.$$

By (E.4),

$$C_i \left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (C_i)^{b_2}(1+b_2)\right)} \left(1 + e^{\frac{C_t + C_i}{\lambda - C_t - C_i} + 1 - V_t}\right)\right) = \lambda,$$

$$\Longrightarrow C_i \left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (C_i)^{b_2}(1+b_2)\right)} \left(1 + e^{\frac{C_i\left(1+e^{V_t - V_i + r\left(b_0 + b_1 (C_i)^{b_2}(1+b_2)\right)}\right)}{\lambda - C_i\left(1+e^{V_t - V_i + r\left(b_0 + b_1 (C_i)^{b_2}(1+b_2)\right)}\right)} + 1 - V_t}\right)\right) = \lambda. \tag{E.5}$$

We make the following observations for the equality (E.5). First, when $C_i = 0$, the LHS $= 0 < \lambda$. Second, there exists a unique $\bar{C}_i \in (0, \lambda)$ such that

$$\bar{C}_i \left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (\bar{C}_i)^{b_2}(1+b_2)\right)}\right) = \lambda. \tag{E.6}$$

Third, as C_i increases from 0 to $\bar{C}_i$, the LSH of (E.5) strictly increases and tends to infinity. Therefore, there exists a unique $C_i \in (0, \bar{C}_i)$ which solves (E.5). Let C_i^* denote that solution and by recalling (E.4), we make the following definition:

$$C_t^* := C_i^* e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}. \tag{E.7}$$

We want to derive a condition under which the unique maximizer of the objective function, (C_t^*, C_i^*), is feasible. First, $C_t^* \wedge C_i^* > 0$ and thus (3.3d) is satisfied. Next, for (3.3c) to hold, we need to show that

$$C_t^* + C_i^* \leq \lambda \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}}. \tag{E.8}$$

By (E.4) and (E.5), the inequality in (E.8) is equivalent to the following:

$$\begin{aligned}
&C_i^* \left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right) \\
&\leq C_i^* \left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} \left(1 + e^{\frac{C_i^*\left(1+e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right)}{\lambda - C_i^*\left(1+e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right)} + 1 - V_t}\right)\right) \\
&\frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \\
&= C_i^* \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} + C_i^* e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \\
&\left(1 + e^{\frac{C_i^*\left(1+e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right)}{\lambda - C_i^*\left(1+e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right)} + 1 - V_t}\right).
\end{aligned}$$

Therefore (E.8) is equivalent to the following inequality.

$$
\begin{aligned}
&C_i^* + C_i^* e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} - C_i^* \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \\
&- C_i^* e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \\
&\leq C_i^* e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} e^{\frac{C_i^*\left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right)}{\lambda - C_i^*\left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right)} + 1 - V_t},
\end{aligned}
$$

which is equivalent to

$$
\begin{aligned}
&\frac{C_i^*}{1 + e^{V_t} + e^{V_i}} + e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} \frac{C_i^*}{1 + e^{V_t} + e^{V_i}} \\
&\leq C_i^* e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} e^{\frac{C_i^*\left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right)}{\lambda - C_i^*\left(1 + e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)}\right)} + 1 - V_t}.
\end{aligned}
$$

Then, for (E.8) to hold, we need,

$$
\begin{aligned}
C_i^* &\leq C_i^* e^{V_t - V_i + r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} \left(e^{\frac{C_i^* + C_t^*}{\lambda - C_t^* - C_i^*} + 1} + e^{\frac{C_i^* + C_t^*}{\lambda - C_i^* - C_t^*} + 1 - V_t + V_i} - 1 \right) \\
\implies e^{V_i - V_t - r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} &\leq e^{\frac{C_i^* + C_t^*}{\lambda - C_t^* - C_i^*} + 1} + e^{\frac{C_i^* + C_t^*}{\lambda - C_i^* - C_t^*} + 1 - V_t + V_i} - 1 \\
\implies 1 + e^{V_i - V_t - r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} &\leq e^{\frac{\lambda}{\lambda - C_t^* - C_i^*}} \left(1 + e^{V_i - V_t}\right), \qquad \text{(E.9)}
\end{aligned}
$$

where the first inequality follows from (E.7). Inequality in (E.9) always holds because

$$
1 + e^{V_i - V_t - r\left(b_0 + b_1 (C_i^*)^{b_2}(1+b_2)\right)} \leq 1 + e^{V_i - V_t} \leq e^{\frac{\lambda}{\lambda - C_t^* - C_i^*}} \left(1 + e^{V_i - V_t}\right)
$$

by (E.8) and the fact that $C_t^* \wedge C_i^* > 0$. So far, we have shown that (3.3c) and (3.3d) hold under the unique maximizer of the objective function of (3.3). Next, we will show that (3.3b) holds when (3.4) is satisfied. For (3.3b), we can write,

$$
m_t C_t^* + m_i C_i^* \leq (m_t \vee m_i)(C_t^* + C_i^*) \leq (m_t \vee m_i) \lambda \frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \leq C,
$$

where the second inequality follows from (E.8) and the last inequality follows from (3.4). Therefore, (3.3b) is also satisfied under (C_t^*, C_t^*), and thus (C_t^*, C_t^*) is the optimal solution to (3.3).

By Theorem 3.3 and because $a_t = a_i = a$, we have

$$p_t^* = \frac{1}{a}\left(V_t - \ln(C_t^*) + \ln(\lambda - C_t^* - C_i^*)\right), \tag{E.10}$$

$$p_i^* = \frac{1}{a}\left(V_i - \ln(C_i^*) - r(b_0 + b_1(C_i^*)^{b_2}) + \ln(\lambda - C_t^* - C_i^*)\right). \tag{E.11}$$

By (E.7) and (E.10), we have

$$p_t^* = \frac{1}{a}\left(V_i - \ln(C_i^*) - r(b_0 + b_1(C_i^*)^{b_2}(1 + b_2)) + \ln(\lambda - C_t^* - C_i^*)\right). \tag{E.12}$$

By (E.11) and (E.12), we obtain the inequality (3.5).

Next, we will show that the optimal price gap increases in r. For given $r \in [0, 1]$, let $C_i^*(r)$ denote the solution to (E.5). From (E.5), it is clear that $C_i^*(r)$ is strictly decreasing in r. Let

$$F(x) := 1 + e^{V_t - V_i + rb_0 + b_1(1+b_2)x}\left(1 + e^{\frac{(\frac{x}{r})^{\frac{1}{b_2}}\left(1 + e^{V_t - V_i + rb_0 + b_1(1+b_2)x}\right)}{\lambda - (\frac{x}{r})^{\frac{1}{b_2}}\left(1 + e^{V_t - V_i + rb_0 + b_1(1+b_2)x}\right)} + 1 - V_t}\right).$$

Then, $F(x)$ is strictly increasing in x when $0 \leq x < r(\bar{C}_i(r))^{b_2}$, where $\bar{C}_i$ is defined in (E.6). By (E.5), we have

$$C_i^*(r)\, F\left(r(C_i^*(r))^{b_2}\right) = \lambda. \tag{E.13}$$

As r increases, $C_i^*(r)$ strictly decreases, and thus $F\left(r(C_i^*(r))^{b_2}\right)$ strictly increases by (E.13). Because F is strictly increasing in r, as r increases, $r(C_i^*(r))^{b_2}$ must strictly increase. Consequently, $r(C_i^*(r))^{b_2}$ is strictly increasing in r. Therefore, by (3.5), the optimal price gap, $p_i^* - p_t^*$, is strictly increasing in r. Furthermore, by (E.7), the optimal capacity ratio, C_t^*/C_i^*, is also strictly increasing in r.

Appendix F

PROOF OF THEOREM 4

Because (3.4) holds, $C^n = nC$, and $\lambda^n = n\lambda$, we have the following,

$$n\lambda(m_t \vee m_i)\frac{e^{V_t} + e^{V_i}}{1 + e^{V_t} + e^{V_i}} \leq nC \quad \forall n \in \mathbb{N}_+,$$

where $\mathbb{N}_+$ denotes the set of strictly positive integers. Consequently, the unique maximizer of (3.3a) is optimal for all $n \in \mathbb{N}_+$ and under both contagion effect and no contagion effect (recall the proof of Theorem 3 in the appendix E). Let $(C_i^{n,R,*}, C_t^{n,R,*})$ denote the optimal capacity allocation and $(p_i^{n,R,*}, p_t^{n,R,*})$ denote the corresponding optimal prices in the nth system under contagion effect. Similarly, let $(C_i^{n,NR,*}, C_t^{n,NR,*})$ denote the optimal capacity allocation and $(p_i^{n,NR,*}, p_t^{n,NR,*})$ denote the corresponding optimal prices in the nth system under no contagion effect. Recall from the proof of Theorem 3 that $(C_i^{n,R,*}, C_t^{n,R,*})$ $((C_i^{n,NR,*}, C_t^{n,NR,*}))$ is the unique maximizer of (3.3a) in the nth system under contagion (no contagion) effect. Let $\pi^{n,R}(A, B)$ denote the value of (3.3a) under the capacity allocation vector (A, B) when there is contagion effect and we let $\pi^{n,R} := \pi^{n,R}(C_i^{n,R,*}, C_t^{n,R,*})$ denote the optimal objective function value. We make the same definition for the case when there is no contagion effect. For notational convenience, we do not use the superscript n when $n = 1$. First, we show how the optimal solution to (3.3) scales with n, that is, we show how the optimal solution changes in n with respect to the benchmark case $n = 1$. Specifically, we prove that $C_i^{n,X,*} = nC_i^{X,*}$, $C_t^{n,X,*} = nC_t^{X,*}$, $p_i^{n,X,*} = p_i^{X,*}$, $p_t^{n,X,*} = p_t^{X,*}$, and $\pi^{n,X} = n\pi^X$ for all $n \in \mathbb{N}_+$ and $X \in \{R, NR\}$. We consider the case when there is a contagion effect because the proof of the case in which there is no contagion effect is the same. By (E.5), in the nth system, we have

$$C_i^{n,R,*}\left(1+e^{V_t-V_i+r\left(b_0+b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}(1+b_2)\right)}\left(1+e^{\frac{C_i^{n,R,*}\left(1+e^{V_t-V_i+r\left(b_0+b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}(1+b_2)\right)}\right)}{n\lambda-C_i^{n,R,*}\left(1+e^{V_t-V_i+r\left(b_0+b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}(1+b_2)\right)}\right)}+1-V_t}\right)\right)=n\lambda.$$

Dividing both sides by n, we have

$$\frac{C_i^{n,R,*}}{n}\left(1+e^{V_t-V_i+r\left(b_0+b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}(1+b_2)\right)}\left(1+e^{\frac{\frac{C_i^{n,R,*}}{n}\left(1+e^{V_t-V_i+r\left(b_0+b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}(1+b_2)\right)}\right)}{\lambda-\frac{C_i^{n,R,*}}{n}\left(1+e^{V_t-V_i+r\left(b_0+b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}(1+b_2)\right)}\right)}+1-V_t}\right)\right)=\lambda.$$

Recall from the proof of Theorem 3 that $C_i^{R,*}>0$ is the unique solution to the above equality for all n. Therefore, $C_i^{n,R,*}/n=C_i^{R,*}>0$ for all $n\in\mathbb{N}_+$ implying that $C_i^{n,R,*}=nC_i^{R,*}$.

By (E.4), in the nth system, we have

$$C_t^{n,R,*}=C_i^{n,R,*}e^{V_t-V_i+r\left(b_0+b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}(1+b_2)\right)}.$$

By dividing both sides by n,

$$\frac{C_t^{n,R,*}}{n}=\frac{C_i^{n,R,*}}{n}e^{V_t-V_i+r\left(b_0+b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}(1+b_2)\right)}=C_i^{R,*}e^{V_t-V_i+r\left(b_0+b_1(C_i^{R,*})^{b_2}(1+b_2)\right)}=C_t^{R,*},$$

where the second equality follows from the fact that $C_i^{n,R,*}=nC_i^{R,*}$, and the third equality follows from (E.4). Then, we have $C_t^{n,R,*}/n=C_t^{R,*}$ implying that $C_t^{n,R,*}=nC_t^{R,*}$. Next, we show that $p_i^{n,R,*}=p_i^{R,*}$ and $p_t^{n,R,*}=p_t^{R,*}$ for all $n\in\mathbb{N}_+$. By

Theorem 2, we have

$$\begin{aligned}
p_t^{n,R,*} &= \frac{1}{a}\left(V_t - \ln\left(C_t^{n,R,*}\right) + \ln\left(n\lambda - C_t^{n,R,*} - C_i^{n,R,*}\right)\right) \\
&= \frac{1}{a}\left(V_t - \ln\left(nC_t^{R,*}\right) + \ln\left(n\lambda - nC_t^{R,*} - nC_i^{R,*}\right)\right) \\
&= \frac{1}{a}\left(V_t + \ln\left(\frac{n(\lambda - C_t^{R,*} - C_i^{R,*})}{nC_t^{R,*}}\right)\right) = \frac{1}{a}\left(V_t - \ln(C_t^{R,*}) + \ln(\lambda - C_t^{R,*} - C_i^{R,*})\right) \\
&= p_t^{R,*}.
\end{aligned}$$

Similarly, by Theorem 2,

$$\begin{aligned}
p_i^{n,R,*} &= \frac{1}{a}\left(V_i - \ln\left(C_i^{n,R,*}\right) - r\left(b_0 + b_1\left(\frac{C_i^{n,R,*}}{n}\right)^{b_2}\right) + \ln\left(n\lambda - C_t^{n,R,*} - C_i^{n,R,*}\right)\right) \\
&= \frac{1}{a}\left(V_i - \ln\left(nC_i^{R,*}\right) - r\left(b_0 + b_1\left(\frac{nC_i^{R,*}}{n}\right)^{b_2}\right) + \ln\left(n\lambda - nC_t^{R,*} - nC_i^{R,*}\right)\right) \\
&= \frac{1}{a}\left(V_i + \ln\left(\frac{n(\lambda - C_t^{R,*} - C_i^{R,*})}{nC_i^{R,*}}\right) - r\left(b_0 + b_1\left(C_i^{R,*}\right)^{b_2}\right)\right) \\
&= \frac{1}{a}\left(V_i - \ln(C_i^{R,*}) - r\left(b_0 + b_1\left(C_i^{R,*}\right)^{b_2}\right) + \ln(\lambda - C_t^{R,*} - C_i^{R,*})\right) \\
&= p_i^{R,*}.
\end{aligned}$$

Because the optimal objective function value of the optimization problem (3.3) when $n = 1$ is $\pi^R = C_t^{R,*}p_t^{R,*} + C_i^{R,*}p_i^{R,*}$, we have $\pi^{n,R} = nC_t^{R,*}p_t^{R,*} + nC_i^{R,*}p_i^{R,*} = n\pi^R$. Next, we will show that $\pi^{n,NR} - \pi^{n,R} = \Theta(n)$. We have

$$\begin{aligned}
\pi^{n,NR} - \pi^{n,R} &= C_i^{n,NR,*}p_i^{n,NR,*} + C_t^{n,NR,*}p_t^{n,NR,*} - \left(C_i^{n,R,*}p_i^{n,R,*} + C_t^{n,R,*}p_t^{n,R,*}\right) \\
&= n\left(C_i^{NR,*}p_i^{NR,*} + C_t^{NR,*}p_t^{NR,*} - C_i^{R,*}p_i^{R,*} - C_t^{R,*}p_t^{R,*}\right) \\
&= n\left(\pi^{NR} - \pi^R\right) \\
&\leq n\pi^{NR}. \qquad \text{(F.1)}
\end{aligned}$$

We also have

$$\pi^{NR}\left(C_i^{NR,*}, C_t^{NR,*}\right) \geq \pi^{NR}\left(C_i^{R,*}, C_t^{R,*}\right) = \pi^R(C_i^{R,*}, C_t^{R,*}) + \frac{C_i^{R,*}}{a} r\left(b_0 + b_1(C_i^{R,*})^{b_2}\right),$$

where the equality follows from the definition of the objective function and the fact that $rR(C_i) = 0$ when there is no contagion. Therefore,

$$\pi^{n,NR} - \pi^{n,R} = n\left(\pi^{NR} - \pi^{R}\right) \geq n\frac{C_i^{R,*}}{a} r\left(b_0 + b_1 (C_i^{R,*})^{b_2}\right). \tag{F.2}$$

By (F.1), (F.2), and the fact that $C_i^{R,*}, a, r, b_1 > 0$, we have $\pi^{n,NR} - \pi^{n,R} = \Theta(n)$.

Appendix G

SCALES OF RISK, PROS, OCAS, AND FCAS

G.1 COVID-19 Risk Perception Scale

Assume that there is a new variant of COVID-19 in which vaccines are not effective.

1. I feel vulnerable to COVID-19 infection.
2. I believe there is a chance that my family members get infected with COVID-19.
3. It is extremely unlikely that I will get infected with COVID-19.
4. Picturing self getting COVID-19 is something I find very hard to do.
5. I believe that COVID-19 poses a serious threat.
6. I worry about getting infected with COVID-19.

A LIKERT Scale of 7 is used, 1: Strongly disagree, 7: Strongly agree. Questions 3 and 4 are reverse coded.

G.2 Prosocial Behavior Intentions Scale

Imagine that you encounter the following opportunities to help others. Please indicate how willing you would be to perform each behavior.

1. Comfort someone I know after they experience a hardship
2. Help a stranger find something they lost, like their key or a pet
3. Help care for a sick friend or relative
4. Assist a stranger with a small task (e.g., help carry groceries, watch their things while they use the restroom)

A LIKERT Scale of 7 is used, 1: Definitely would not do this, 7: Definitely would do this.

G.3 Attitudes Toward Online and Face-to-face Counseling Scales

The next two sets of questions ask about your attitudes toward seeking counseling (psychological) through either of two methods: (a) online counseling (where you would interact with a counselor in real-time using a platform such as Zoom) or (b) face-to-face counseling (where you would go to a counselor's office in person).

Please read the questions carefully because the sets of questions are similar. However, the first 5 pertain to online counseling and the last 5 pertain to face-to-face counseling. There are no "wrong" answers, and the only right ones are the ones you honestly feel or believe. Read each item carefully and indicate your agreement.

Online Counseling:

1. Using online counseling would help me learn about myself.
2. If a friend had personal problems, I might encourage him or her to consider online counseling.
3. I would confide my personal problems in an online counselor.
4. It could be worthwhile to discuss my personal problems with an online counselor.
5. If online counseling were available at no charge, I would consider trying it.

Face-to-face Counseling:

1. Using face-to-face counseling would help me learn about myself.
2. If a friend had personal problems, I might encourage him or her to consider face-to-face counseling.
3. I would confide my personal problems in a face-to-face counseling session.
4. It could be worthwhile to discuss my personal problems with a face-to-face counselor.
5. If face-to-face counseling were available at no charge, I would consider trying it.

A LIKERT Scale of 7 is used, 1: Strongly disagree, 7: Strongly agree.

Appendix H

COMPREHENSION CHECK QUESTIONS

H.1 Study 1

Question 1 is asked in all groups. Question 2.1 is asked in the C1 and IM1 groups, and Question 2.2 is asked in the HP and HP $\times$ IM1 groups.

1) Which of the following is incorrect (false) about the scenario provided?
a) Existing vaccines are not effective against this new variant.
b) It poses a risk to people of all ages.
c) Your health problem requires urgent care.

2.1) Which of the following is incorrect (false) about the appointment types?
a) After a face-to-face appointment, there is a risk of getting infected.
b) After an online appointment, there is a chance of needing a face-to-face follow-up appointment.
c) The price of a face-to-face appointment is higher than the price of an online appointment.

2.2) Which of the following is incorrect (false) about the appointment types?
a) After a face-to-face appointment, there is a risk of getting infected.
b) After an online appointment, there is a chance of needing a face-to-face follow-up appointment.
c) The price of a face-to-face appointment is equal to the price of an online appointment.

H.2 Study 2

Both Question 1 and Question 2 are asked in all groups.

1) Which of the following is incorrect (false) about the scenario provided?
a) Existing vaccines are not effective against the new virus.
b) The earliest available appointment date for both options is the same.
c) You have been feeling dizzy and fatigued.

2) Which of the following is incorrect (false) about the information provided?
a) After a face-to-face appointment, there is a chance of getting infected with the new virus.
b) After an online appointment, there is a chance of needing a face-to-face appointment.
c) If you make an online appointment, you definitely wait less to get treated compared to a face-to-face appointment.

H.3 Study 3

Both Question 1 and Question 2 are asked in all groups.

1) Which of the following is incorrect (false) about the scenario provided?
a) Existing vaccines are not effective against the new virus.
b) The new virus only affects older people.
c) The university's health center suggests you to see a doctor at a hospital.

2) Which of the following is incorrect (false) about the information provided?
a) During a hospital visit, there is a chance of getting infected with the new virus.
b) After a face-to-face appointment, your health condition is definitely treated.
c) You never need to make a face-to-face appointment after an online appointment.

H.4 Study 4

Which of the following is incorrect (false) about the information provided?

a) You have dizziness, fatigue, and difficulty sleeping.

b) At the healthcare facility, there is a chance of getting infected with a respiratory virus.

c) After a telemedicine appointment, you may need to make an in-person appointment and visit the healthcare facility.

d) Telemedicine appointments are always free.

Appendix I

ATTENTION CHECK QUESTIONS

1) Please select “Somewhat agree” for the following question. This is an attention check.

Based on the above information, which option have you been asked to select?

a) Strongly disagree

b) Disagree

c) Somewhat disagree

d) Neither agree nor disagree

e) Somewhat agree

f) Agree

g) Strongly agree

2) Assume the following scenario:

Reason: Seeing the doctor to get treatment

Option 1: In-person appointment

Option 2: Telemedicine appointment

For this question, please write 2025 as your payment amount. This is an attention check.

Based on the text you read above, what payment amount have you been asked to write?

Appendix J

ROBUSTNESS CHECKS

Table J.1: Study 1. ANOVA Results for PROS, RISK, OCAS, and FCAS

		SS	df	MS	F	p-value	η^2
PROS	Between Groups	1.716	3	0.572	0.753	0.521	0.008
	Within Groups	224.906	296	0.760	-	-	
	Total	226.622	299	-	-	-	
RISK	Between Groups	0.571	3	0.190	0.202	0.895	0.002
	Within Groups	278.233	296	0.940	-	-	
	Total	278.803	299	-	-	-	
OCAS	Between Groups	0.201	3	0.067	0.050	0.985	0.001
	Within Groups	399.711	296	1.350	-	-	
	Total	399.912	299	-	-	-	
FCAS	Between Groups	1.256	3	0.419	0.356	0.785	0.004
	Within Groups	347.909	296	1.175	-	-	
	Total	349.165	299	-	-	-	

Table J.2: Study 1. Results of the logistic regression model in (4.1). Specifications differ in comprehension checks. Specification (2) is significant under a significance level of 0.1. In both specifications, coefficients (standard errors) are shared with the significance levels, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variable: Channel Choice	(1)	(2)
Sample	CC=1 or 2	CC=2
Participants	300	193
Higher Price (HP)	0.401	0.483
	(0.348)	(0.431)
Infection Message (IM1)	0.915***	0.856**
	(0.348)	(0.432)
Higher Price × Infection Message (HP × IM1)	−0.573	−0.858
	(0.492)	(0.609)
RISK	0.489**	0.465**
	(0.196)	(0.228)
RISK × Infection Message (RISK × IM1)	0.015	0.169
	(0.267)	(0.318)
OCAS	0.175	0.050
	(0.130)	(0.167)
FCAS	−0.476***	−0.308*
	(0.145)	(0.185)
PROS	0.089	0.179
	(0.154)	(0.198)
Age	−0.043	−0.051
	(0.092)	(0.117)
Female	0.160	0.031
	(0.269)	(0.340)
Online Experience	0.205	0.457
	(0.284)	(0.370)
Intercept	1.418	1.094
	(2.280)	(2.953)

Table J.3: Study 2. ANOVA Results for RISK, OCAS, and FCAS

		SS	df	MS	F	p-value	η^2
RISK	Between Groups	5.359	2	2.680	2.815	0.062	0.019
	Within Groups	281.784	296	0.952	-	-	
	Total	287.144	298	-	-	-	
OCAS	Between Groups	0.949	2	0.474	0.373	0.689	0.003
	Within Groups	376.164	296	1.271	-	-	
	Total	377.113	298	-	-	-	
FCAS	Between Groups	2.490	2	1.245	1.225	0.295	0.008
	Within Groups	300.856	296	1.016	-	-	
	Total	303.346	298	-	-	-	

Table J.4: Study 2. Chi-Square Test Results for WRT

	χ^2	df	p-value	Cramer's V
WRT	14.495	2	< 0.001	0.220

Table J.5: Study 2. Pairwise Chi-Square Comparisons for WRT

	χ^2	df	p-value	Cramer's V
IM2 vs. C2	11.911	1	< 0.001	0.243
IM2 vs. WM	9.613	1	0.002	0.219
C2 vs. WM	0.122	1	0.727	0.025

Table J.6: Study 2. Results of the logistic regression model in (4.2). Specifications differ in comprehension checks. In both specifications, coefficients (standard errors) are shared with the significance levels, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variable: Channel Choice	(1)	(2)
Sample	CC=1 or 2	CC=2
Participants	299	223
Infection Message (IM2)	0.251	0.022
	(0.336)	(0.413)
Wait Time Message (WM)	0.287	0.157
	(0.329)	(0.397)
RISK	0.321*	0.267
	(0.192)	(0.220)
RISK × Infection Message (RISK × IM2)	−0.474	−0.089
	(0.297)	(0.341)
OCAS	0.462***	0.339**
	(0.145)	(0.167)
FCAS	−0.438***	−0.407*
	(0.164)	(0.220)
WRT	1.703***	2.317***
	(0.280)	(0.347)
Age	0.216**	0.175
	(0.101)	(0.122)
Female	−0.242	−0.175
	(0.293)	(0.361)
Online Experience	−0.057	−0.511
	(0.286)	(0.359)
Intercept	−5.543**	−4.257
	(2.469)	(3.041)

Table J.7: Study 2. Results of the logistic regression model in (4.2) without WRT. Specifications differ in comprehension checks. In both specifications, coefficients (standard errors) are shared with the significance levels, *** $p < 0.01$, ** $p < 0.05$, *

Dependent Variable: Channel Choice	(1)	(2)
Sample	CC=1 or 2	CC=2
Participants	299	223
Infection Message (IM2)	0.586^{*}	0.446
	(0.309)	(0.356)
Wait Time Message (WM)	0.310	0.082
	(0.305)	(0.346)
RISK	0.304^{*}	0.231
	(0.175)	(0.189)
RISK × Infection Message (RISK × IM2)	-0.581^{**}	-0.294
	(0.274)	(0.303)
OCAS	0.397^{***}	0.306^{**}
	(0.134)	(0.146)
FCAS	-0.528^{***}	-0.522^{***}
	(0.151)	(0.192)
Age	0.236^{**}	0.185^{*}
	(0.093)	(0.107)
Female	-0.171	-0.020
	(0.271)	(0.314)
Online Experience	0.195	-0.163
	(0.264)	(0.308)
Intercept	-4.555^{**}	-2.842
	(2.263)	(2.635)

Table J.8: Study 2. Results of the logistic regression model in (4.2) in the weighted data according to the inverse probability weighting. Specifications differ in comprehension checks. In both specifications, coefficients (standard errors) are shared with the significance levels, *** $p < 0.01$, ** $p < 0.05$, *

Dependent Variable: Channel Choice	(1)	(2)
Sample	CC=1 or 2	CC=2
Participants	299	223
Infection Message (IM2)	0.192	0.015
	(0.179)	(0.204)
Wait Time Message (WM)	0.289*	0.139
	(0.175)	(0.202)
RISK	0.351***	0.256**
	(0.101)	(0.110)
RISK × Infection Message (RISK × IM2)	−0.703***	−0.319*
	(0.161)	(0.178)
OCAS	0.431***	0.340***
	(0.080)	(0.087)
FCAS	−0.546***	−0.565***
	(0.089)	(0.114)
Age	0.239***	0.180***
	(0.054)	(0.061)
Female	−0.108	0.045
	(0.158)	(0.182)
Online Experience	0.146	−0.214
	(0.151)	(0.176)
Intercept	−4.582***	−2.556*
	(1.297)	(1.514)

Table J.9: Study 3. ANOVA Results for RISK, OCAS, and FCAS

		SS	df	MS	F	p-value	η^2
RISK	Between Groups	0.948	2	0.474	0.504	0.605	0.003
	Within Groups	334.699	356	0.940	-	-	
	Total	335.647	358	-	-	-	
OCAS	Between Groups	0.611	2	0.305	0.201	0.818	0.001
	Within Groups	540.674	356	1.519	-	-	
	Total	541.284	358	-	-	-	
FCAS	Between Groups	2.109	2	1.055	1.053	0.350	0.006
	Within Groups	356.470	356	1.001	-	-	
	Total	358.579	358	-	-	-	

Table J.10: Study 3. Chi-Square Test Results for WRT

	χ^2	df	p-value	Cramer's V
WRT	2.902	2	0.234	0.087

Table J.11: Study 3. Results of the logistic regression model in (4.3). Specifications differ in comprehension checks. In both specifications, coefficients (standard errors) are shared with the significance levels, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variable: Channel Choice	(1)	(2)
Sample	CC=1 or 2	CC=2
Participants	359	243
Infection Message (IM3)	0.272	0.299
	(0.272)	(0.338)
Convenience Message (CM)	0.647**	0.832**
	(0.279)	(0.341)
RISK	−0.012	−0.323*
	(0.153)	(0.188)
RISK × Infection Message (RISK × IM3)	0.507**	0.834**
	(0.255)	(0.323)
Travel Time	0.456	0.497
	(0.354)	(0.451)
Travel Time × Convenience Message (Travel × CM)	−1.423**	−1.017
	(0.585)	(0.683)
OCAS	0.253**	0.276**
	(0.108)	(0.129)
FCAS	−0.312**	−0.142
	(0.134)	(0.169)
WRT	0.294	0.171
	(0.229)	(0.280)
Age	0.112	0.152
	(0.084)	(0.108)
Female	−0.136	−0.019
	(0.243)	(0.295)
Online Experience	0.442	−0.246
	(278)	(0.357)
Private Car Use	−0.471*	−0.556*
	(0.262)	(0.337)
Intercept	−1.941	−3.814
	(1.964)	(2.504)

Table J.12: Study 4. ANOVA Results for RISK, OCAS, and FCAS

		SS	df	MS	F	p-value	η^2
RISK	Between Groups	8.748	2	4.374	2.640	0.072	0.007
	Within Groups	1225.966	740	1.657	-	-	
	Total	1234.715	742	-	-	-	
OCAS	Between Groups	0.893	2	0.446	0.287	0.751	0.001
	Within Groups	1150.332	740	1.555	-	-	
	Total	1151.224	742	-	-	-	
FCAS	Between Groups	1.412	2	0.706	0.592	0.554	0.002
	Within Groups	883.160	740	1.193	-	-	
	Total	884.573	742	-	-	-	

Table J.13: Study 4. Chi-Square Test Results for WRT

	χ^2	df	p-value	Cramer's V
WRT	5.680	2	0.058	0.087

Table J.14: Study 4. Results of the logistic regression model in (4.4). Specifications differ in comprehension checks. In both specifications, coefficients (standard errors) are shared with the significance levels, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variable: Channel Choice	(1)	(2)
Sample	CC=0 or 1	CC=1
Participants	743	674
Infection Message (IM4)	0.386**	0.289
	(0.195)	(0.202)
Convenience Message (CM2)	0.603***	0.543***
	(0.196)	(0.203)
RISK	0.142*	0.112
	(0.079)	(0.082)
RISK × Infection Message (RISK × IM4)	−0.060	−0.022
	(0.131)	(0.137)
Travel Time	−0.423**	−0.396*
	(0.212)	(0.222)
Travel Time × Convenience Message (Travel × CM2)	0.454	0.245
	(0.365)	(0.385)
OCAS	0.510***	0.483***
	(0.091)	(0.094)
FCAS	−0.419***	−0.393***
	(0.097)	(0.101)
WRT	0.512***	0.495***
	(0.160)	(0.167)
Age	0.006	0.002
	(0.006)	(0.006)
Female	−0.055	−0.096
	(0.162)	(0.170)
Online Experience	0.551***	0.492***
	(0.173)	(0.181)
Private Car Use	0.006	−0.059
	(0.215)	(0.229)
Higher Education	−0.045	−0.103
	(0.191)	(0.200)
Intercept	−1.694***	−1.374**
	(0.550)	(0.578)