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Multichannel Healthcare: Impact of Asynchronous Telemedicine Adoption on Patient Flow

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Abstract. ***Problem definition***: This paper studies a multichannel healthcare system where physicians diagnose patients and prescribe treatment in-person or through asynchronous telemedicine (AT), a widely adopted yet relatively under-explored form of telemedicine. In collaboration with physicians at the Veterans Healthcare Administration (VHA), we examine the impact of introducing an AT channel on the existing in-person channel and on overall system performance. ***Methodology/results***: VHA implemented AT at select clinics in the state of Georgia in 2012. Using a difference-in-differences design, we find that the introduction of the AT channel led to a sorting process whereby more complex patients were seen in the in-person channel. AT implementation led to a 20% increase in recommended visit time and an 8.5% increase in required clinical resources for in-person consultations. In addition, the adoption of AT resulted in higher throughput—more patients seen by the specialists per month across both channels. Using a fixed-effects model we find a reduction in average wait time for in-person referrals (37.5%), and for the most common medically necessary procedure (43%) despite an increase in the total number of consultations at the specialist clinic. We attribute the improved efficiency to early patient triage, better match between patient needs and treatment modality, and reduction of setup and switching costs in physicians' workflow. ***Managerial implications***: This paper contributes to our understanding of a rapidly expanding form of healthcare delivery: multichannel healthcare with in-person and AT channels. Our results suggest that healthcare managers and physicians can adopt AT to improve overall system efficiency. At the same time, they should take into account the additional impact of AT on the in-person channel when making capacity decisions and developing guidance on patient referrals.

Supplemental Material: The online appendix is available at https://doi.org/10.1287/msom.2022.0235.

Keywords: multichannel healthcare • telemedicine • queue segmentation

1. Introduction

For the better part of the last two decades, telemedicine has received a *cautious* welcome (Perednia and Allen 1995) from physicians. As a new type of healthcare delivery, telemedicine had limited empirical evidence on its accuracy and reliability. This sentiment, however, has changed dramatically in the last few years as the underlying technology matured and physicians became more familiar with it. The expansion of reimbursement from insurance companies has also supported the adoption of telemedicine (Patel et al. 2021). By 2020, more than 50 U.S. health systems had leveraged telemedicine to provide consultations with physicians (Hollander and Carr 2020). Examples include Jefferson Health, Mount Sinai, Kaiser Permanente, and the Cleveland Clinic.

Telemedicine's sudden but widespread adoption, combined with its evolving nature, has created a gap in the literature. There are different modalities of telemedicine (synchronous or asynchronous) that are often implemented in parallel to existing in-person care delivery, resulting in multichannel healthcare systems (Lee et al. 2022). The need to better understand the operational implications of telemedicine and its interaction with the in-person channel is echoed by the medical community (Kahn 2015, Gordon et al. 2017, Tuckson et al. 2017, Barnett et al. 2021), as well as scholars in the healthcare operations field (Dai and Tayur 2020).

Our study focuses specifically on asynchronous telemedicine (AT). Also referred to as store-and-forward, AT captures clinically relevant samples and data, and digitally transmits this information to a remote site where it is reviewed by health professionals who do not interact with the patient (Deshpande et al. 2009). AT is used across a wide range of specialties (Abbatemarco et al. 2021, Nguyen et al. 2021, Nekhlyudov et al. 2022, Gordon et al. 2023). Its usage has also become increasingly sophisticated, resulting in higher levels of diagnostic equivalency (Pak et al. 2007, Portnoy et al. 2016, Trettel et al. 2018, Sommer and Blumenthal 2020, Khayretdinov and Rubakova 2023). Diagnostic equivalency allows physicians to effectively replace some in-person visits with AT.

To provide timely insights, we collaborate with academic physicians to study an early adoption of AT that created a multichannel healthcare system. In particular, we study the following questions of practical importance to physicians. First, does the introduction of an AT channel impact the existing in-person channel? Specifically, does the addition of an AT channel lead to patient segmentation or do the two channels have a similar patient mix? Second, what are the system level implications—how does the adoption of AT affect the overall healthcare system's throughput? Finally, does AT impact timely access to care, including access to upstream care?

Our research setting is the Veterans Health Administration (VHA), an integrated healthcare system managed by the U.S. Department of Veterans Affairs (VA). VHA adopts a common practice for outpatient care—patients first see primary care physicians (PCPs) and then, if necessary, get referred to specialists. In September 2012, VHA implemented AT at seven primary clinics in the state of Georgia. These clinics, which serve as our treatment group, were able to refer patients to asynchronous or in-person consultations with specialists post-AT adoption. Our control group consists of clinics that did not adopt AT and referred patients only for in-person consultations. This clinic-specific adoption allows us to use a quasi-experimental difference-in-differences (DID) approach to estimate the effect of the AT adoption.

We find that introducing the AT channel led to a sorting process whereby more complex patients were seen in the in-person channel. Specifically, in-person patients referred from the treatment group require an additional 20% in recommended time for consultations and an 8.5% increase in clinical resources. We also find that the introduction of AT increased the overall patient throughput among specialists. Specialists were able to provide consultations to an additional 11 new patients every month from referring clinics that adopted AT. This increase was driven by AT consultations, which inherently take only a fraction of the time required for an in-person visit. Despite the increase in the throughput rate, we find no evidence of upstream congestion at the specialist level. We find that average wait time for the first in-person appointment with the specialist decreased by 15 days (compared with the original 40) as some patients were redirected to the AT channel.

We attribute the improvements in overall system capacity and wait time to a better matching of patient needs with care modality. From our discussions with physicians on their working practices, we learned that they typically review AT cases in dedicated time blocks. The segmentation of patients in different care delivery queues allows physicians to batch different procedural tasks, resulting in an increase of short-term focus and a decrease in setup costs for physicians.

To the best of our knowledge, we are among the first to empirically study the effects of asynchronous telemedicine in a multichannel healthcare system, where physicians may diagnose patients either remotely or in-person. The existing empirical literature has mainly studied the telemedicine channel in isolation, whereas clinical research on telemedicine has often focused on the diagnostic equivalency of remote and in-person channels.

2. Literature Review

This work builds on and contributes to two fundamental streams of the healthcare operations literature: queuing and productivity. Our paper also adds to the literature on telemedicine. Furthermore, our research setting—a multichannel healthcare system—allows us to draw insights on multichannel operations.

2.1. Queues in Healthcare Operations

The first stream of research relevant to our work is queue pooling and separation, especially in a healthcare setting. Queue pooling reduces wait time because the customer is directed to the first available server rather than wait for an assigned server to become available (Eppen 1979, Bassamboo et al. 2010). However, separate queues can be more efficient when arrivals have different processing requirements (Rothkopf and Rech 1987, Mandelbaum and Reiman 1998) or when the system faces rare and difficult tasks (Mandelbaum and Reiman 1998). This is often the case for queues in a healthcare setting (Green and Nguyen 2001).

We add to the existing literature by considering a relatively new kind of queue separation in a healthcare setting: an asynchronous telemedicine queue and an in-person queue in a multichannel healthcare system.

2.2. Productivity

AT adoption changes physician workflow, and the resulting multichannel healthcare system creates new challenges and opportunities. Physicians that deliver care over multiple channels will experience additional, cross-channel setup and switching costs. However, if each channel consists of a relatively homogeneous patient population, within-channel setup and switching costs will decrease.

Prior studies have shown that switching costs negatively impact productivity in various contexts. For example, KC (2014) finds that multitasking in a healthcare context can increase productivity by reducing the idle time of physicians but could decrease productivity by incurring excessive toggling and higher setup costs. KC and Tushe (2021) show that switching costs between different working locations are also negatively associated with productivity.

AT also enables discretion on task selection and task batching. Deviation from random task assignment and discretionary task selection tend to have a negative impact on physician productivity (Ibanez et al. 2018, KC et al. 2020). Our setup is closer to Staats and Gino (2012), who find productivity benefits from short-term specialization within a day and task variety over longer periods of time.

2.3. Telemedicine

2.3.1. Medical Literature on Telemedicine. Clinical research on telemedicine has traditionally focused on diagnostic equivalency to the in-person channel and patient satisfaction with remote care. Telemedicine has also been shown to improve physician training by providing access to a wider range of patient groups (Yeung et al. 2018).

Studies across multiple specialties provide support on the diagnostic equivalency of telemedicine and in-person channels (Pak et al. 2007, Portnoy et al. 2016, Trettel et al. 2018, Sommer and Blumenthal 2020, Khayretdinov and Rubakova 2023). Admittedly, equivalency is more difficult to achieve, or even study, in some specialties (Chua et al. 2001, McConnochie et al. 2006, Nelson and Palsbo 2006). We note that more recent studies show stronger support for the diagnostic equivalency, which could reflect improvements in the underlying technology.

Despite evidence of diagnostic equivalency between remote and in-person channels, the medical literature has identified several risks that require further research (Gordon et al. 2017, Tuckson et al. 2017). These risks potentially include more follow-up encounters (Kahn 2015), lapses in incidental care that is usually provided during in-person consultations (Keleshian et al. 2017, Baranowski et al. 2020), and telemedicine-specific barriers to access (George et al. 2024). Gaps in follow-up care can also occur when the diagnosing physician is different from the treatment physician (Martin et al. 2015).

2.3.2. Medical Literature on Asynchronous Telemedicine. AT was widely adopted during the COVID-19 pandemic across specialties that do not, at face value, seem good candidates for it. Nekhlyudov et al. (2022) and Gordon et al. (2023) describe instances of physicians rethinking the cancer care continuum in light of the pandemic and implementing AT. Abbatemarco et al. (2021) describe the incorporation of both synchronous and asynchronous telemedicine in the care of multiple sclerosis patients. Nguyen et al. (2021) provide a review of AT literature in healthcare outlets and cite interventions for patients with diabetes, blood pressure, urinary tract infections, and conjunctivitis. Patterson (2021) describes the increased use of teleneurology during the COVID-19 pandemic.

Our study provides crucial insights on AT by studying an implementation outside the context of the pandemic and without any of the associated restrictions on the in-person channel.

2.3.3. Operations Management Literature. Using analytical models, operations management (OM) researchers have identified potential tradeoffs from the introduction of telemedicine. Bavafa et al. (2021) demonstrate that the effect of telemedicine depends on the compensation of e-visits relative to offline visits. Çakıcı and Mills (2021) show that high accessibility of teletriage leads to higher emergency department arrival rate and higher costs. Rajan et al. (2019) find that telemedicine can lead to a reduction in physical sites of healthcare providers, leaving some patients worse off.

Empirical work on electronic communication between physicians and patients has identified a negative effect on clinic productivity (Bavafa et al. 2018). We note that electronic communication is intended as a supplement to physician work. In our study, AT is intended as a replacement for in-person consultations.

Our work complements the literature by providing empirical evidence of AT's unintended consequences on in-person patient visits, as well as its positive impact on overall system performance.

2.4. Multichannel Operations

Work on multichannel operations has looked at the benefits of introducing an online channel (Aflaki and Swinney 2021), the interaction between the online and physical channel (Ofek et al. 2011), and the restructuring of physical locations after the introduction of the online channel (Gao and Su 2018). Prior research has focused on the retail space and the results can be difficult to translate to a healthcare setting. First and foremost, decision making in the healthcare field, although impacted by financial incentives (Scott et al. 2011), is heavily guided by professional norms that emphasize patient care (Ludewigs et al. 2022). Second, although customers self-select channels and transactions in the retail space, patient self-selection is restricted by formal mechanisms such as patient triage in in-patient settings, referral requirements in out-patient settings, and insurance reimbursement rules that restrict access to physicians, procedures and medication.

We complement the existing literature by studying multichannel operations in a healthcare context.

3. Research Setting

3.1. VHA

Our research setting is part of the VHA, a large government-run healthcare system that serves U.S. veterans and their families. Unlike Medicare or Medicaid, the other major public healthcare programs in the United States, the VHA is not an insurance provider. Instead, it operates its own clinics and hospitals across the country and employs physicians and staff directly. Although the VHA sometimes pays for outside care using a fee-per-service system, patients need permission in advance and they are responsible for higher copays (Rasmussen and Farmer 2023).

The unique structure of the VHA provides several advantages. First, it allows us to track patients over multiple encounters. Second, we can rule out the possibility that system changes will lead to patients exiting the VHA. Third, the VHA compensates physicians with a fixed salary, which allows us to safely assume our observed effect will not be the result of financial incentives at the visit level. Finally, the VHA has been an early adopter of telemedicine (Russo et al. 2016), making it an ideal setting for studying the early adoption of telemedicine and drawing lessons that can be applied to other healthcare systems. We provide additional details on VHA's operations below.

3.1.1. Patient Flow Within the VHA. VHA has built a network of 171 medical centers and 1,113 outpatient care clinics. Patients choose their primary clinic but cannot choose their primary care physician (PCP) within that clinic (VHA 2022).

PCPs within VHA act as gatekeepers to specialist resources, similar to PCPs in other centralized healthcare systems such as the National Health Service in the United Kingdom (Fortney et al. 2005) or Health Maintenance Organizations in the United States (Kapur et al. 2000). These systems offer low financial barriers to patient use (Bachman and Freeborn 1999) in exchange for restrictions on access to specialists, including via self-referrals (Forrest and Reid 1997).

Referral decisions are complex, show significant variation across physicians (Forrest and Reid 1997), and are influenced by patient self-advocacy (Brody 1980). Nevertheless, in centralized systems like the VHA, PCPs wield a larger influence on patient flow through the healthcare system, including the rate of referral to specialists.

3.1.2. Physician Compensation Within the VHA. Our research setting allows us to disentangle the potential effect of financial incentives on physician behavior. Medical decision making is driven by the fiduciary duty of care (Ludewigs et al. 2022) but can also be influenced by the size and structure of financial incentives (Scott et al. 2011). Although U.S. physicians generally rely on volume-based compensation (Reid et al. 2022), physicians within the VHA system are compensated primarily through a fixed salary. Variable compensation (performance pay) is capped by legislation at 7.5% of the physicians' annual pay from the prior year (Fink 2006).

Because physicians in our study setting are salaried and do not receive volume-based financial incentives, we can attribute findings on their referral behavior to core medical decision making.

3.2. Empirical Setting Within the VHA

In this research, we focus on the medical specialty of dermatology. The VHA operates a single dermatology specialist clinic in the state of Georgia, which is based in Atlanta, and sees patients referred from across the state. For simplicity, we refer to the dermatology specialist clinic as *the specialist* for the rest of the paper.

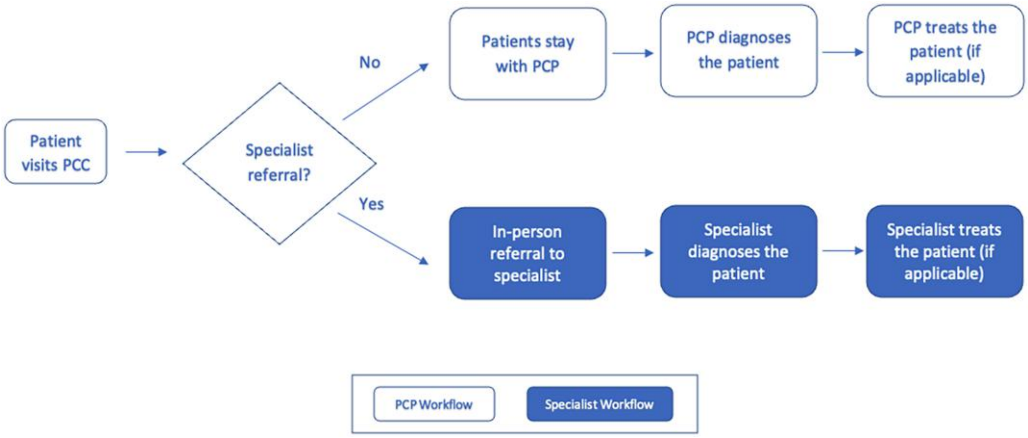
A patient with a dermatological concern follows the standard workflow for outpatient care. They first visit a VHA primary care clinic. The PCP will then either treat the patient or refer them to the specialist. Before the adoption of the AT system, all patients were referred through the in-person channel.

3.2.1. AT Roll-out. VHA began implementing the AT system in June 2012. Specifically, some primary care clinics were equipped with imaging tools that record high-resolution images of the patients' skin conditions. These images, together with PCP notes, could then be forwarded to the specialist in the form of an electronic referral. Between June 2012 and September 2012, physicians were trained on the use of the underlying technology. The active use of the AT channel started in September 2012, which serves as our intervention month.

The AT specialist consultation is intended to be equivalent to, and replace, the first in-person specialist visit. Specialists are expected to diagnose, and if necessary, prescribe treatment to patients asynchronously. Procedure codes for AT consultations during the study period (and until very recently) were the same as for in-person visits. For example, a new referral consultation that requires straightforward medical decision making will receive the CPT code 99201, whether the consultation occurred in-person or through AT. Any subsequent in-person visits (e.g., to receive treatment) will be coded as follow-up visits. Even if the AT consultation is inconclusive, and the patient is asked to come for an in-person visit, the AT consultation is considered the first patient "visit" with the specialist. We note that all follow-up visits after the first referral take place in person. In other words, AT is limited to only new referral consultations.

Primary care clinics that were equipped with asynchronous telemedicine could refer patients to the specialist for an in-person visit or an AT visit. PCPs from

Figure 1. (Color online) VA Referral System Before AT Adoption



these clinics had wide discretion on the choice of channel. Figures 1 and 2 show the referral process before and after the AT adoption, respectively.

3.2.2. Control and Treatment Clinics. Control and treatment groups are constructed based on the availability of AT. Seven primary care clinics were selected for AT implementation based on their geographical distance to the specialist and serve as the treatment group in our analyses. Our control group consists of two referral sources. The first referral source is the primary care clinic that is affiliated with the main VHA hospital of the region. Although this clinic is operationally indistinguishable from clinics in the treatment group, it was not selected for AT implementation because of its vicinity to the specialist. The second referral source in the control group consists of referrals from other, nondermatological specialist clinics or the hospital itself.

To alleviate any potential concern about the selection of the treatment group, we confirm with physicians and administrators within the VHA system that patient characteristics were not part of the decision-making criteria. Instead, the adoption decision was based on the geographical location of primary clinics. Summary statistics in Table 1 show that patients from the treatment and control groups are indeed similar before the AT adoption. Furthermore, we validate the parallel trend assumption visually in Figure 3 and formally in Section 6.4.

Figure 2. (Color online) VA Referral System After AT Adoption

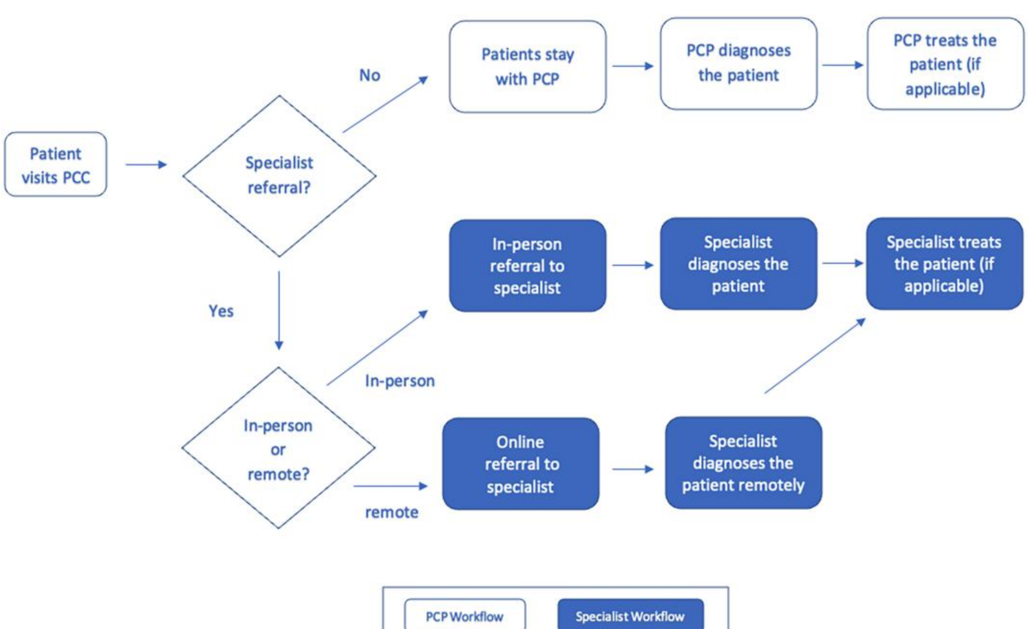


Table 1. Preintervention Summary Statistics

	Control group		Treatment group		
Variable	Mean	Standard deviation	Mean	Standard deviation	*t*-test
Complexity Level	2.14	0.03	2.00	0.10	
Planned Time	32.22	0.48	30.13	1.36	
RVU Work	1.29	0.03	1.23	0.06	
RVU Facility	1.62	0.02	1.55	0.06	
Age	64.64	1.18	64.33	0.81	
Gender (Male)	1.90	0.03	1.97	0.01	**
Race (Black)	0.27	0.04	0.13	0.03	***

Notes. The table summarizes data from September 2011 to September 2012. Treatment group refers to those clinics that adopted AT in 2012, whereas Control croup refer to those clinics that did not adopt AT in 2012. For each variable, we compare the average monthly score of the treatment and control group before the intervention.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4. Hypotheses Development

4.1. Patient Segmentation

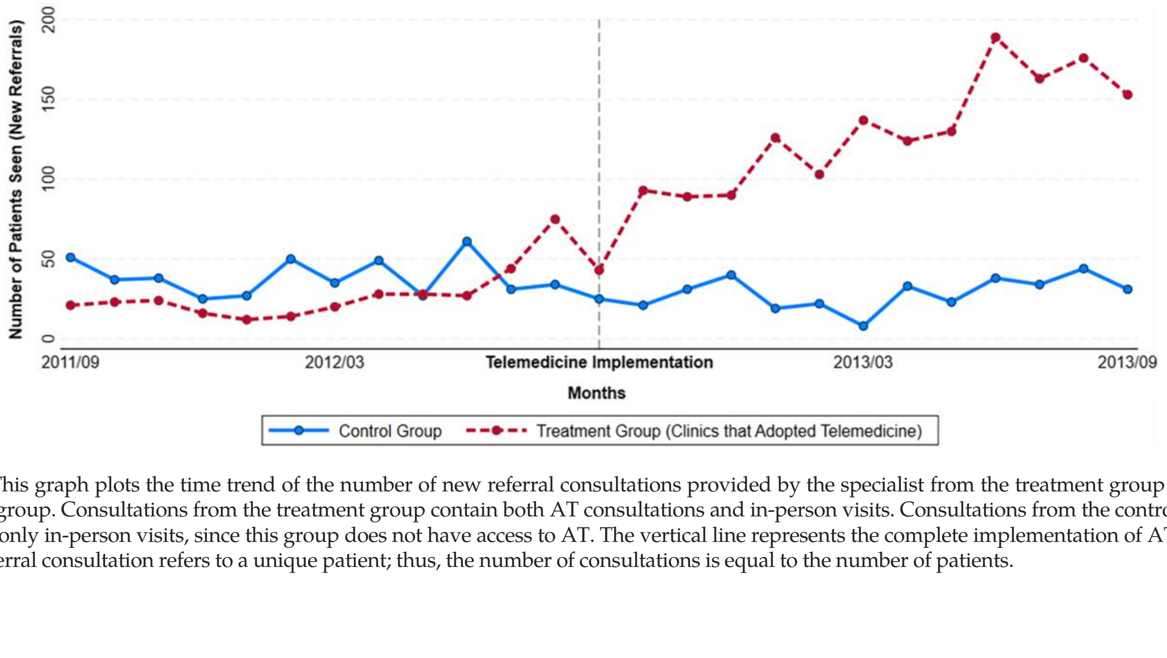
We first discuss how the introduction of AT as a parallel referral channel can lead to channel-specific patient segmentation. The differentiation of patient classes into different channels can happen inadvertently or can follow the decision-making practices of physicians.

Segmentation can occur inadvertently when medical conditions are unevenly distributed across patient groups and AT is restricted to one or several groups of patients. For example, telemedicine has traditionally targeted patients in medically underserved and rural areas (Dussault and Franceschini 2006). At the same time, recent findings suggest that urban patients utilize telemedicine at a higher rate (Sun and Wang 2023). If medical conditions are geographically unevenly distributed, the AT and in-person channels will then see different patient classes. However, in our empirical setting, patient characteristics are comparable between the treatment and control groups, as shown in Table 1, and validated in the formal tests in our robustness checks in Section 6.4.

4.1.1. Case for More Complex Patients Through the AT Channel. Patients can also be guided into different channels by healthcare providers. PCPs may refer complex patients or cases through AT to expedite diagnosis and treatment if they believe AT has a faster turnaround time (Patterson et al. 2010). They can also refer more complex patients through AT if they believe that these patients are more likely to miss an in-person specialist appointment (Chan and Green 2013).

4.1.2. Case for More Complex Patients to the In-Person Channel. On the other hand, PCPs may refer more complex patients through the in-person channel if they believe that direct interaction with the specialist might

Figure 3. (Color online) Total Number of Consultations Provided by the Specialist from September 2011 to September 2013 Through the *In-Person* or *AT* Channel



Notes. This graph plots the time trend of the number of new referral consultations provided by the specialist from the treatment group and the control group. Consultations from the treatment group contain both AT consultations and in-person visits. Consultations from the control group contain only in-person visits, since this group does not have access to AT. The vertical line represents the complete implementation of AT. Every new referral consultation refers to a unique patient; thus, the number of consultations is equal to the number of patients.

allow for a more comprehensive investigation of the patient's conditions (Pan et al. 2008). They can also refer more complex cases through the in-person channel as a way of managing their own relationship with their patients, who might have misgivings about telemedicine in general (Anand et al. 2011). Finally, PCPs might want to avoid becoming intermediaries for complex patients and specialists, fearing a large amount of communication from either side (Murphy et al. 2012). To protect their own time, PCPs will then refer more complex patients through the in-person channel.

On balance, we expect that the introduction of AT will result in more complex patients being seen in-person.

Hypothesis 1. *Complex patients will be referred at higher rates through the in-person channel after the adoption of AT.*

4.2. System Throughput

The introduction of new healthcare delivery channels can have important implications for system throughput. However, the size and direction of these effects is not clear. In this section, we describe how AT may affect system efficiency and, subsequently, throughput.

Fundamentally, AT redistributes care resources across two channels: the existing in-person channel, and the newly introduced AT channel. Managing multiple channels can present operational challenges, as well as opportunities for efficiency gains. The net effect on operational performance depends on whether the drivers of operational gains can outweigh the factors for operational inefficiencies.

On the one hand, the introduction of a new, parallel AT channel can reduce specialist capacity since building, adopting, and learning a new system inherently requires time and effort (Berg 2001). As specialists deliver care over two separate channels, each with its own characteristics, cross-channel setup costs and switching costs increase (KC 2014). In addition, the introduction of AT may also lead to duplicate efforts and repeat encounters (Pan et al. 2008). Finally, Parkinson's law, the idea that work expands to fill the time available, has been observed in many service settings, including healthcare (Hasija et al. 2010). Such tendencies could have the effect of consuming any freed-up resources, without any net operational throughput gains.

On the other hand, several factors point to improved efficiency and patient throughput under AT adoption. In principle, an AT consultation should require less time than in-person one because the specialist does not interact directly with the patient and relies on information summarized by the PCP in the electronic referral file. Patient introductions, discussions, and follow-on questions are eliminated, reducing the time spent per consultation. The sorting process resulting from the introduction of AT can lead to more homogeneous patient populations in each channel. Reducing within-channel patient variability could thus decrease switching costs from patient to patient and facilitate task batching within channels. Lastly, specialists working on the AT channel may also experience fewer interruptions from other care providers, such as nurses (Chisholm et al. 2000) because reviewing patient files typically requires minimal to no interaction with other staff.

Hypothesis 2. *The introduction of the AT channel increases system throughput.*

4.3. Timely Access to Care

The effect of AT on wait times for in-person consultations can be impacted by efficiencies and inefficiencies similar to those described above in Section 4.2. If the introduction of AT introduces inefficiencies, the specialist will be able to provide fewer in-person consultations and wait times for an appointment will increase. Conversely, if the AT implementation frees up specialist time, we should expect specialists to provide more in-person consultations, thus reducing wait times.

Wait times can change even if the number of in-person consultations provided by the specialist does *not* change. Consider a scenario where some patients that were previously seen in-person are diverted to the AT channel and AT consultations require significantly less time than an in-person consultation. In this scenario, specialists can continue to provide the same number of in-person consultations, but every new in-person referral will join a shorter queue and thus experience a shorter wait time. Because we generally expect AT consultations to be less time consuming, we hypothesize the following.

Hypothesis 3. *The introduction of the AT channel reduces wait time for in-person consultations.*

5. Data and Identification Strategy

5.1. Data

Our data come from the VHA and specifically from the only dermatology specialist clinic in the state of Georgia. We are able to observe all specialist consultations (in-person or AT), as well as patient characteristics for these consultations (e.g., age, gender, race). We are also able to distinguish between new referrals and follow-up visits, as well as the source and the modality of new referrals (in-person or AT). As a reminder, all follow-up specialist visits after the initial referral occur in person.

5.1.1. Patient and Consultation Characteristics. Patients are analyzed using derivatives of *current procedural terminology (CPT)* codes, which are developed by the American Medical Association (AMA) and are assigned to every procedure performed by physicians in outpatient settings (Dotson 2013). Referrals to the specialist are recorded as first-time consultations at the specialist level. All medical specialties use the same CPT codes for first-time consultations of new patients (Hill 2003), allowing us to draw specialty-neutral conclusions on the impact of AT.

Building on the CPT codes and existing literature on patient complexity (Murthy et al. 2023), we assign a *complexity score* from one to five to all first-time patients, with a higher score reflecting more complex patients. A complexity score of five is rare and did not occur in our data during the study period. As part of their description from the AMA, CPT codes are also associated with a *recommended time* for each consultation, which translates complexity into an intuitive measure.

CPT codes are also associated with *relative value units (RVUs)*, which were developed as the basis of Medicare's reimbursement formula (Nurok and Gewertz 2019), but are also used by private insurance providers (Luong et al. 2018). RVUs take into account visit duration and patient complexity, but they are a separate and broader measure that captures resource utilization at the physician level (work RVU) and clinic level (facility RVU). Both measures of RVUs help us understand potential financial implications that arise from AT adoption. Table 1 shows the average statistics on key patient characteristics pre-AT adoption across the control group and treatment group.

5.1.2. Specialist Capacity and Productivity. Changes at the specialist level are analyzed using two key measures: number of first-time consultations provided by the specialist and wait times for an in-person consultation.

We aggregate the number of new referral consultations provided by the specialist—across the AT channel and the in-person channel—by referral clinic and month. This variable represents the specialist's *throughput rate*. Note that every new referral consultation refers to a unique patient; thus, we can use the terms patient, visit, or consultation interchangeably. Figure 3 shows the trend in throughput rate, based on referring source. The trend shows that before the AT adoption, the throughput rate evolved in a similar pattern between referring clinics in the treatment group and in the control group. After the AT adoption, however, the throughput rate of the treatment group is significantly higher.

Figure 4 shows the number of *in-person* new referral consultations by the specialist during the same period, based on referring source. The graph indicates that the number of patients seen by the specialist through the in-person channel remained steady before and after the AT adoption, for both the treatment and control groups. Comparing Figures 3 and 4, we can see that the increase in the number of patients seen by the specialist is driven by the AT channel. Figures 3 and 4 together suggest that the parallel trend assumption is not violated in our DID setup. We also test for the parallel trend formally in our robustness checks in Section 6.4. As shown by Figure 3, and empirically validated in Section 6.2, the specialist clinic was able to accommodate an increased number of new referral consultations, indicating an increase in system capacity.

Next, we consider the average wait time for the new referral in-person consultation, and for biopsy and cryotherapy, common follow-up procedures. Note that the wait time for the first in-person consultation refers to the time between a PCP's referral and the specialist consultation. The wait time for a procedure refers to the time between the first consultation with the specialist (which can be in-person or through AT) and when the procedure is performed.

5.2. Identification Strategy

5.2.1. DID Specification. A quasi-experimental DID design serves as our main identification strategy. We use the DID design to study AT's effect on patient complexity for the *in-person* channel and the aggregated throughput rate (of both AT and in-person channels) based on the referral source.

This identification strategy exploits the unilateral AT adoption at referral sources. As a reminder, primary care clinics that adopted AT and can refer patients both through AT and in person form our treatment group. Clinics that did not adopt AT and can only refer patients through the in-person channel form our control group. Also recall that AT adoption was not guided by patient characteristics but followed the physical location of the clinics. This setup allows us to use a DID design to estimate the treatment effect of the AT adoption.

Our empirical analysis on patient complexity studies the effect of AT on the average patient complexity of in-person visits only. Because there are no patients referred through AT before the intervention, we cannot use a DID specification to evaluate complexity in the AT channel. In other words, we estimate the change in the average complexity of new patients referred through the in-person channel, when AT becomes available as a parallel referring channel.

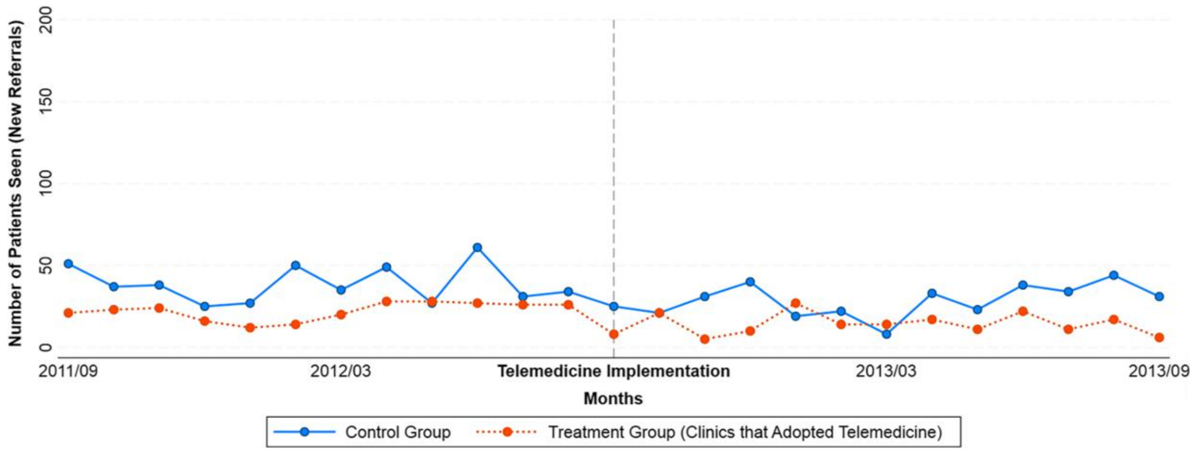
Our empirical analysis on throughput looks at the total number of new patients consulted by the specialist, based on referral source. Because AT consultations and in-person consultations of new patients are considered equivalent, we are able to construct monthly throughput measures before and after the intervention for both control and treated clinics. In plain terms, we investigate whether the specialist is able to provide more patient consultations after AT is introduced.

We conduct our analyses at the clinic-month level and include both clinic and time fixed effects using the following specification:

$$Y_{ct} = \beta \, Treated_c \times Adoption_t + \gamma_t + \delta_c + \epsilon_{ct}, \qquad (1)$$

where c denotes the clinic, t denotes the month, Y_{ct}

Figure 4. (Color online) Total Number of Consultations Provided by the Specialist from September 2011 to September 2013 Through the *In-Person* Channel Only



Notes. This graph plots the time trend of the number of *in-person* new referral consultations provided by the specialist from the treatment group and the control group. The vertical line represents the complete implementation of AT. Every first-time consultation refers to a unique patient. Every new referral consultation refers to a unique patient; thus the number of consultations is equal to the number of patients.

represents the outcome variable for clinic c during month t, γ_t is the time fixed effect at the monthly level, δ_c is the clinic fixed effect that captures the time-invariant characteristics of clinic c, and ϵ_{ct} is the error term. The dummy variable $Treated_c$ equals one if clinic c adopted telemedicine and zero otherwise. The dummy variable $Adoption_t$ equals one if month t occurs after the telemedicine began active use (that is, the month of September 2012) and zero otherwise. The coefficient β estimates the effect of the telemedicine adoption. Note that the main effect of $Treated_c$ and $Adoption_t$ are absorbed by the clinic and time fixed effects, respectively.

In our analyses, we tested three different DID specifications: (1) with no fixed effects, (2) with only clinic fixed effects, and (3) with both clinic and time fixed effects.

5.2.2. Fixed Effect Specification. We leverage fixed effect models to study telemedicine's effect on timely access to care. Specifically, we study how the adoption of AT affects patient waiting time for in-person visits, for diagnostic procedures (biopsy), and for treatment procedures (cryo therapy). As a reminder, the wait time for in-person consultations captures the days between the PCP referral and the actual specialist visit, whereas the wait time for procedures captures the time between the first specialist consultation and the subsequent procedure.

Note that we opt for a fixed effect model because any variations in the specialist's capacity will impact all patients, regardless of referral source. For example, if improvements in capacity reduce wait times, the benefit will not be limited to only patients referred from treated clinics. A DID would have been preferred, due to the robustness in the handling of unobserved characteristics. However, in our setting, the use of DID is inappropriate. Instead, we change our empirical specification to be able to include patient-specific controls to account for potential endogeneity as following:

$$Y_{cpt} = \beta Adoption_{pt} + \mathbf{X}_{cpt} + \gamma_t + \delta_c + \epsilon_{cpt}, \qquad (2)$$

where Y_{cpt} represents wait time, $\mathbf{X}_{cpt}$ represents the patient-level control variables, c denotes the referring clinic, t denotes the month, γ_t is the time fixed effect at the monthly level, δ_c is the clinic fixed effect that captures the time-invariant characteristics of the referring clinic c, and ϵ_{cpt} is the error term. The dummy variable $Adoption_{pt}$ equals one if patient p's visit at month t occurs after telemedicine began active use (that is, the month of September 2012) and zero otherwise.

6. Results

As a reminder, all referrals from PCPs to the specialist refer to first-time consultations. In addition, an in-person visit is equivalent to an AT consultation, as discussed in Section 3.2. Therefore, when talking about PCP referrals, we can use the terms patient, visit, or consultation interchangeably.

6.1. Patient Segmentation

In this section, we report estimations from Equation (1)—our DID specification—on complexity score, recommended visit time, and RVUs. We use the 12 months prior to the AT adoption as the pretreatment period and the 12 months following the AT adoption as the posttreatment period.

Table 2 reports the effect of AT adoption on patients' complexity level in the in-person channel. The analyses

Table 2. Impact of AT on Patient Complexity Score

	Dependent variable: *Average Patient Complexity Score*		
Variables	(1)	(2)	(3)
Treated × Adoption	0.217***	0.221***	0.204***
	(0.038)	(0.036)	(0.045)
Clinic fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
Observations	143	143	143
R^2	0.026	0.026	0.166

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (1). The coefficients for the DID specification with no fixed effects, with only clinic fixed effects, and with both clinic and time fixed effects are presented in columns (1)–(3), respectively.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

yield consistent results across the three models with no fixed effect, only clinic fixed effects, and both clinic and time fixed effects. After the AT adoption, there is a statistically significant increase in average complexity score of in-person patients referred from the treated clinics. The coefficient of the interaction term in column (3) suggests an increase of 0.2 points in patient complexity score, which takes values in the range of one to five.

To better understand the implications of the increase in complexity, we turn to the other two measures: recommended time for a visit and RVUs. Table 3 reports the effect of AT adoption on the average recommended time for patient visits. The analyses also yield consistent results across the three different DID specifications. After the AT adoption, physicians need to allocate significantly more treatment time to in-person patients referred from clinics that adopted AT compared with patients referred from clinics that did not. The coefficient of the interaction term in column (3) suggests an increase of three minutes in the time specialists need for their consultations. Prior to the AT adoption, the specialists assigned 15 minutes to each visit based on historical averages. Therefore, this result suggests that physicians need 20% more time for in-person patients after the AT adoption, an economically significant increase.

Table 3. Impact of AT on Recommended Time for a Patient Consultation

	Dependent variable: *Average Recommended Time for a Patient Consultation*		
Variables	(1)	(2)	(3)
Treated × Adoption	3.254***	3.308***	3.053***
	(0.566)	(0.534)	(0.688)
Clinic fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
Observations	143	143	143
R^2	0.026	0.026	0.163

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (1). The coefficients for the DID specification with no fixed effects, with only clinic fixed effects, and with both clinic and time fixed effects are presented in columns (1)–(3), respectively.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4. Impact of AT on Relative Value Units (RVU)—Work

	Dependent variable: *(log) Relative Value Units*		
Variables	(1)	(2)	(3)
Treated × Adoption	0.107***	0.106**	0.089*
	(0.040)	(0.042)	(0.044)
Clinic fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
Observations	143	143	143
R^2	0.028	0.028	0.194

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (1). The coefficients for the DID specification with no fixed effects, with only clinic fixed effects, and with both clinic and time fixed effects are presented in columns (1)–(3), respectively.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Tables 4 and 5 report the effect of AT adoption on the average Work RVU and Facility RVU. In-person patients referred from clinics that adopted AT utilize more clinical resources post-AT adoption.

As a reminder, our empirical analysis on patient complexity above only studies in-person consultations, because there are no patients referred through AT before the intervention, thus depriving us from an appropriate preadoption control group to study AT patients' complexity. However, to better understand complexity across channels, we compare the postadoption complexity of patients referred from treated clinics. The average complexity score is 2.01 for in-person consultations versus 1.00 for AT consultations. *t*-tests show that the difference between the two groups is statistically significant.

Table 5. Impact of AT on Relative Value Units (RVU): Facility

	Dependent variable: *(log) Relative Value Units*		
Variables	(1)	(2)	(3)
Treated × Adoption	0.136***	0.141***	0.126***
	(0.035)	(0.034)	(0.0038)
Clinic fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
Observations	143	143	143
R^2	0.038	0.038	0.167

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (1). The coefficients for the DID specification with no fixed effects, with only clinic fixed effects, and with both clinic and time fixed effects are presented in columns (1)–(3), respectively.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6.2. System Throughput

Next, we provide estimation results from Equation (1)—our DID specification—on the throughput rate at the specialist clinic. The throughput rate captures the number of patients seen by the specialist clinic each month, based on referral source. It is important to clarify that these numbers refer to the number of consultations actually provided by the specialist and not the number of referrals. The throughput rate includes consultations through both in-person and AT.

In this analysis, we adjust for the full time equivalent (FTE) level at the specialist clinic for AT referrals to calculate a common measure for capacity. All existing specialist FTEs became responsible for both AT and in-person referrals after AT adoption. However, postadoption, and in anticipation of operational frictions in AT, the specialist clinic added resources that were dedicated exclusively to the AT channel. To ensure the number of consultations is truly comparable across referring channels, we divide the total number of AT consultations by the ratio of FTEs available to AT to FTEs available to in-person consultations.

Results in Table 6 suggest that after the AT adoption, the throughput rate of the treatment group becomes significantly higher compared with that of the control group. The coefficients of the interaction term are consistent across specifications, showing that the AT adoption leads to a higher throughput of 11 more patients per month from the treated group that received telemedicine. In other words, the specialist clinic is able to provide consultations to 11 additional patients, in-person or through AT, referred from treated clinics. As Figure 3 shows, this increase is mainly attributable to the increase in patients through the AT channel.

6.3. Timely Access to Care

In this section, we discuss results on wait time for in-person visits and procedures at the specialist level after the AT adoption. Tables 7–9 report the estimation results using the fixed effect model in Equation (2).

Table 7 shows AT's impact on the wait time for an in-person appointment from the time of referral. The analyses yield consistent results across specifications. The results indicate that after the AT adoption, the average wait time for in-person visits was reduced significantly. The average wait for a specialist appointment before the introduction of AT was 40 days. The results in column (3) therefore suggest a 37.5% reduction in wait time in the in-person referral channel.

We attribute this decrease in wait times for an in-person visit to a reduction in new in-person referrals as some patients are redirected to the AT channel. As Figure 4 shows, the volume of new in-person consultations that the specialist clinic provides every month remains the same. In addition, the specialist clinic resources dedicated to in-person consultations remains the same as discussed in Section 6.2. However, the rate of new referrals made by the primary care clinics every month decreased, as shown by Figure A.1 in the online supplement. In other words, new patients referred by the primary care clinics join a shorter queue of patients waiting to be seen in-person by the specialist.

Tables 8 and 9 report the change in wait time for biopsy and cryotherapy procedures, respectively. Results in Table 8 show that on average, a patient's wait time for a biopsy, a diagnostic procedure, did not change significantly after the AT adoption. However, the wait time for cryotherapy, a procedure administered to patients with a clear need for medical intervention decreased by 13 days (Table 9). The average wait time for cryotherapy before the AT adoption was 30 days.

Together, these results show that the increase in complexity and throughput from the AT adoption does not create upstream congestion at the specialist level. Instead, there is an overall increase in capacity at the system level. Specialists, which in our setting have large discretion on how to use this additional capacity,

Table 6. Impact of AT on the FTE-Adjusted Clinic Throughput Rate

	Dependent variable: *FTE-Adjusted Throughput Rate*		
Variables	(1)	(2)	(3)
Treated × *Adoption*	10.76***	11.09***	11.67***
	(4.012)	(3.984)	(4.508)
Clinic fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
Observations	184	184	184
R^2	0.189	0.189	0.351

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (1). The coefficients for the DID specification with no fixed effects, with only clinic fixed effects, and with both clinic and time fixed effects are presented in columns (1)–(3), respectively.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7. Impact of AT on Wait Time for In-Person Visits

	Dependent variable: *Wait Time for In-Person Visits*		
Variables	(1)	(2)	(3)
Adoption	−11.080***	−11.269***	−15.615***
	(2.372)	(2.419)	(6.174)
Patient level controls	Yes	Yes	Yes
Clinic fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
Observations	1,282	1,282	1,282
R^2	0.039	0.053	0.108

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (1). The coefficients for the DID specification with no fixed effects, with only clinic fixed effects, and with both clinic and time fixed effects are presented in columns (1)–(3), respectively.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8. Impact of AT on Wait Time for Biopsy

	Dependent variable: *Wait Time for Biopsy*		
Variables	(1)	(2)	(3)
Adoption	−0.104	−0.734	1.190
	(3.289)	(3.442)	(11.11)
Patient level controls	Yes	Yes	Yes
Clinic fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
Observations	383	383	383
R^2	0.023	0.051	0.238

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (1). The coefficients for the DID specification with no fixed effects, with only clinic fixed effects, and with both clinic and time fixed effects are presented in columns (1)–(3), respectively.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

allocate a part of it to cryotherapy, a time sensitive procedure. Biopsies, however, are less urgent and are not prioritized. Consequently, they do not benefit from the additional capacity available.

These results address one of the key concerns of the medical community regarding the adoption of telemedicine: Although initial consultations via telemedicine might seem more efficient, they might make access to follow-up care less efficient (Kahn 2015, Tuckson et al. 2017).

6.4. Robustness Checks

In this section, we report the results of several robustness tests. Specifically, we check the parallel trends assumption and conduct falsification tests to ensure that our estimated effects are not idiosyncratic.

6.4.1. Parallel Trend. Our DID design is valid if there are no underlying time-dependent trends in outcomes unrelated to the policy change. We test the parallel trend assumption formally by expanding Equation (1) to

Table 9. Impact of AT on Wait Time for Cryotherapy

	Dependent variable: *Wait Time for Cryotherapy*		
Variables	(1)	(2)	(3)
Adoption	−5.890*	−6.068*	−13.41**
	(3.101)	(3.260)	(5.806)
Patient level controls	Yes	Yes	Yes
Clinic fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
Observations	616	616	616
R^2	0.011	0.035	0.124

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (2). The coefficients for the DID specification with no fixed effects, with only clinic fixed effects, and with both clinic and time fixed effects are presented in columns (1)–(3), respectively.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

estimate the treatment effect month by month before the AT adoption. Specifically, we replace $Adoption_t$ with the dummy variable $Time_\tau^t$, where $\tau \in -12, -11, -10, \ldots, -2, -1, 0$ because we use 12 months before the AT adoption as the pretreatment period; $Time_\tau^t = 1$ if $\tau = t$ and 0 otherwise, indicating the relative τth month before the adoption in the following specification:

$$Outcome_{ct} = c + Treated_c + \sum_{\tau=-12}^{-1} Time_\tau^t + \sum_{\tau=-12}^{-1} \beta_\tau Treated_c \times Time_\tau^t + \gamma_t + \delta_c + \epsilon_{ct}. \quad (3)$$

The benchmark is September 2012, the month when AT went into active use. The coefficients β_{-12} to β_{-1} identify month-by-month pretreatment differences between the treatment and control groups. We expect these coefficients to be insignificant.

Tables B.1 and B.2 in the online supplement present the estimation results. They show no pretreatment differences in the trends between treated and control clinics. Furthermore, results are consistent across all outcome variables used in the DID specification. Together, these results suggest that the parallel trend assumption is not violated.

6.4.2. Placebo Test. Next we conduct a falsification test to show that our estimate effects are not an artifact of seasonality—we test whether the same treatment effects also occurred in the treated clinics in 2011. We repeat the same analyses specified in Equation (1) using data in 2011 for the same time window used in 2012. If our results simply capture seasonality, we should be able to find significant effects in 2011 as well.

Tables B.3 and B.4 in the online supplement present the estimation results. We conduct the analyses for all outcome variables whose model specification relies on Equation (1). We report the results with no fixed effect and with both clinic and time fixed effects. The results of placebo tests are consistent among different specifications—the placebo-treated average treatment effects are insignificant, implying that there were no significant changes in the difference between the treated and untreated clinics in patient complexity score, planned time for a patient visit, or either RVU score in the previous year.

In our analyses of number of patients seen by the specialist, we include both in-person and telemedicine patients. However, the AT channel did not exist in 2011. Therefore, instead of repeating the DID analysis using data in 2011, we perform the analysis only using in-person patients. This test helps us confirm that the increased number of consultations indeed comes from the telemedicine channel. Table B.5 in the online supplement presents the results, which suggest that the number of referred patients seen by the specialist through the in-person channel did not change significantly.

6.4.3. Interspecialty Referrals. In our DID setting, the control group comprises of two main referral sources: a primary care clinic and interspecialty referrals. To validate the construction of the control group, we have argued that the selection of the clinics is independent from patient characteristics, and we have explicitly shown that clinics from the control group and the treatment group are not significantly different before the telemedicine adoption. With that being said, one might wonder whether PCP referral patients are inherently different from interspecialty referrals and thus biasing our results.

To address this concern, we perform our DID specification in Equation (1), including clinics from only one referral source in the control group at a time. Tables B.6 and B.7 in the online appendix present results of using only the primary care clinic that did not adopt AT, and only interspecialty referrals as the control group, respectively. Both results are consistent with our main analysis, alleviating potential concerns of referral sources in the control groups.

6.5. Post Hoc Analyses

6.5.1. Impact on Revisits. In this section, we examine whether the introduction of the AT channel had any effects on quality of patient care, as indicated by the need for a patient revisit. We posit that patients seen in the AT channel receive adequate diagnosis and care. Furthermore, given that these patients are generally lower risk compared with those seen in-person, we would expect fewer complications and therefore fewer revisits relative to patients seen in-person. We evaluate revisits for all patients who received their first specialist consultation (in-person or through AT) during the first year of AT implementation. The dependent variable is the number of patient revisits within one, two, or three years following their first consultation with the specialist. The explanatory variable takes the value of one if the patient's first consultation was through AT and zero otherwise.

Results in Table 10 align with our expectations—patients who received their first consultation through AT have lower revisit rates on average, compared with patients who were initially seen through the in-person channel. By testing different time windows up to three years, we also assuage concerns that the AT patients might have low revisit rates because their symptoms are misdiagnosed, resulting in larger complications further down the road.

Table 10. Revisit Rates Based on Referral Source

	Dependent variable: *Number of visits within the selected time period*		
Variables	One year	Two years	Three years
AT for first visit	−0.765***	−0.750***	−0.742***
	(0.025)	(0.025)	(0.027)
Patient level controls	Yes	Yes	Yes
Clinic fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	1,819	1,819	1,819
R^2	0.552	0.517	0.491

Note. Estimated coefficients and robust standard errors (in parentheses) of revisit rates within one year, two years, and three years of first specialist consultation.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

6.5.2. Heterogeneous Effect of Distance. Next, we examine whether distance is an important driver of patient usage of AT. In particular, we posit that longer travel distances to in-person clinics can deter in-patient visits while increasing the attractiveness of the AT channel. To examine the heterogeneous effect of distance on patient flow, we split referring clinics that were equipped with AT into two groups: those within 40 miles of the specialist clinic (suburban clinics), and those that are more than 40 miles away than the specialist clinic (rural clinics). We then rerun our analysis on complexity but using a difference-in-difference-in-differences model with two treatment groups. Results in Table 11 show that the PCPs tendency to refer more complex patients through the in-person channel increases in clinics that are further away from the specialist. This suggests that considerations of referrals that were discussed in Section 6.1 are moderated by the effect of distance. In other words, the differential effects of telemedicine compared with in-person care are magnified when the patients incurs greater travel distance for in-person visits.

7. Discussion

In this paper, we study a timely and important issue in healthcare operations—the effect of introducing an asynchronous telemedicine channel (AT) and its impact on the resulting multichannel healthcare system. Healthcare systems that can provide diagnosis and prescribe treatment through multiple channels have gained the trust of physicians in recent years. Since the COVID-19 pandemic, the popularity of such systems has seen rapid growth, partially due to the removal of regulatory restrictions that limited telemedicine reimbursements to only patients living in medically underserved areas. Therefore, changes in telemedicine's role and adoption level have necessitated a better understanding of the system-wide impact of telemedicine.

Collaborating with physicians at the VHA, we provide empirical evidence of how the AT channel impacts in-person visits. Our findings not only address concerns of VHA physicians but also provide managerial insights for the healthcare sector regarding the adoption of telemedicine. We find that introducing an AT channel led to a sorting process whereby more complex patients are seen in the in-person channel. We also find an overall improvement in capacity, captured as an increase in the

Table 11. Heterogeneous Impact of Distance

	Dependent variables: *Patient Segmentation Measures, and Throughput*				
Variables	Complexity	Planned time	RVU work	RVU facility	Throughput
SuburbanTreated × *Adoption*	0.167***	2.499***	0.003	0.043*	11.85**
	(0.0352)	(0.527)	(0.027)	(0.020)	(4.411)
RuralTreated × *Adoption*	0.271***	4.065***	0.155***	0.129***	11.31*
	(0.069)	(1.032)	(0.044)	(0.029)	(5.166)
Clinic fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	143	143	143	143	184
R^2	0.168	0.168	0.214	0.204	0.352

Notes. Estimated coefficients and robust standard errors (in parentheses) from Equation (1). All DID specifications include both clinic and time fixed effects.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

throughput rate and a reduction in wait time for in-person visits.

Despite the overall improvement in operational performance and overall patient flow, our results also raise further questions. Specifically, does the increase in specialist referrals lead to an increase in excessive medical spending? Our data limitations preclude us from determining whether the increase in care consumption was attributed to medically necessary care, or to unneeded wasteful resource usage. In general, assessing the potential overuse and waste of medical resources is a topic of significant importance, and we point this out as an area of future research.

This work has several limitations. Although the majority of our analysis relies on a quasi-experimental difference-in-difference approach, our analysis of wait time for initial consultations and follow-up procedures relies on a fixed-effect model because system capacity changes would affect all patients. We recognize that relying solely on the fixed-effect model may raise concerns about endogeneity. With that being said, we address this by carefully controlling for relevant patient characteristics, as well as clinic and time fixed effects in our model. The results provide relevant and valuable information to hospital managers and physicians regarding telemedicine adoption. We also identify an increase in the clinical resources required for the in-person channel after the adoption of an asynchronous telemedicine channel. However, our empirical setting makes it difficult to analyze the complexity of financial implications for clinics that adopt multichannel healthcare.

We study a healthcare system in which there are no individual financial incentives because employees are salaried and whose patients rarely seek treatment elsewhere. The lack of financial incentives provides a cleaner identification of physician behavior. Nevertheless, the impact of multichannel healthcare might be more complicated in systems with competing financial incentives and potential patient abandonment of the system. In our study setting, patient preference is exogenous to the adoption of AT by the VHA. However, in many other settings, patient preference can also drive the sorting process of patients into the telemedicine or the in-person channel. Examining the role of patient preference on the operational implications of telemedicine adoption could be an area of further inquiry. Last, our study focuses specifically on asynchronous telemedicine, which encapsulates the effects of remote as well as asynchronous care delivery. Separating the effects of asynchronous review from remote review could be interesting and important as an additional avenue for future research.

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