Impact of Telehealth and Process Virtualization on Healthcare Utilization

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Abstract

Technological advancements and the COVID-19 pandemic have catapulted process virtualization in many sectors, including healthcare, where telehealth has enabled the significant digital transformation of care delivery. Although telehealth has been proposed as a potential solution to improve access to care and restrain runaway healthcare costs, it can increase spending if telehealth visits lead to new types of resource utilization. Drawing on the lens of Process Virtualization Theory, we study the impact of telehealth on healthcare utilization by examining visit-level patient data of telehealth use in facilitating e-visits with healthcare providers. On average, a telehealth visit reduces the number of future outpatient visits by 13.6% (or 0.15 visits), equal to a reduction of $239 in total cost within 30 days after the visit. Our results suggest that the benefits of telehealth use are observed primarily among diseases with high virtualization potential. Specifically, patients with mental health, skin disorders, metabolic, and musculoskeletal diseases, exhibit a significant reduction of 0.21 outpatient visit per quarter (an equivalent cost reduction of $179) when they are treated via telehealth, suggesting a *substitution effect* with respect to traditional clinic visits. Our research identifies the boundary conditions that determine the nuanced impact of telehealth on care utilization and shows that its effectiveness depends on the process virtualization potential of different diseases. Our findings have several practical and theoretical implications for fostering telehealth use in a value-based healthcare environment, especially for diseases with high virtualization potential where telehealth use should be promoted to bend the cost curve.

Keywords: Telehealth, process virtualization theory, diseases, outpatient, visit, cost, resource utilization.

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1 INTRODUCTION

As the use of digital technologies has hastened in recent years, physical interactions are increasingly being replaced by virtual interactions, enabling the virtualization of business processes (Fiol and O'Connor 2005, Gartner 2022). Global investment in the digitization and virtualization of business processes has reached $1.8 trillion in 2022, an increase of 17.6% over 2021, and is projected to grow 16.6% annually between 2021-2025 (IDC 2022). Notable examples of successful digital transformations that gave rise to process virtualization include online shopping, digital marketing, online dating, and distance learning (Berguerand 2022, Fertik 2020, Sickler 2022, Weiler 2020). However, until recently, the healthcare sector in the United States has been slow to adopt such digital transformations for healthcare processes, making it one of the last avenues yet to realize the full potential of process virtualization.

However, the COVID-19 pandemic has accelerated the digital transformation of healthcare, driven by a shift to virtual care (Landi 2021). This shift triggered a total of $21.3 billion in investments toward digital health startups in 2021 in the United States, a trend that is projected to continue in the future (Landi 2021). Telehealth has been the primary catalyst behind the virtualization of healthcare with the goal of improving healthcare access, costs, and outcomes (Bestsennyy et al. 2021). Telehealth can help transform traditional healthcare delivery and increase access to specialized care, helping patients to monitor lifestyle changes and providers to triage patients in real-time. Bestsennyy et al. (2021) estimated that up to $250 billion in US healthcare spending could be substituted with more cost-effective telehealth. However, virtualization of care through telehealth is not straightforward, as evidenced by a recent survey which reported that 64% of physicians do not favor telehealth for reasons ranging from convenience to experience (Cordina et al. 2022).

In practice, telehealth has been mainly utilized for treating specific diseases, such as psychiatry, dermatology, and endocrinology (Cordina et al. 2022). Since care virtualization via telehealth may be subject to frictions caused by medical requirements, telehealth may not be suitable for every disease class. However, the reasons as to why telehealth has not been adequately utilized for patient care remain largely unanswered (Bestsennyy et al. 2021). Similarly, research on care virtualization to treat patients with specific conditions has been lacking, except for a few types of mental health and drug abuse conditions (Huskamp et al. 2018). While understanding the requirements of care virtualization through telehealth is crucial, the economic impact of care virtualization is also of interest to policymakers and practitioners (Adler-Milstein et al. 2014, Overby et al. 2010, Rajan et al. 2019). In recent years, government agencies have called for proper justification of the benefits of telehealth use, as observed in a report by the U.S. Senate Committee on Finance, which argued that "…. traditionally telehealth has been viewed as a tool to improve access to services, but interest is growing to see if telehealth has the potential to reduce health care costs ...." (Senate.gov 2015). A comprehensive analysis of the impact of telehealth and the mechanisms involved in virtualizing care through telehealth, is long overdue and requires systematic empirical investigation. At a broader level, the information systems literature has also called for more research to investigate virtualization of e-businesses, especially along three dimensions: (a) understand the virtualization of processes, (b) how virtual processes are likely to be used, and (c) the consequences of process virtualization (Overby et al. 2010). In our study, we address this call in the context of telehealth and pose our research questions as follows:

RQ1: What is the impact of telehealth-enabled process virtualization on future healthcare utilization, as measured by the number of outpatient visits and costs?

RQ2: Does the impact of process virtualization through telehealth vary based on the degree of virtualizability of different disease types? i.e., How does variation in the process virtualizability of different diseases impact the link between telehealth-enabled process virtualization and healthcare utilization?

RQ3: What information technology capabilities of telehealth facilitate the differential impact of telehealth on future utilization?

Our research objectives are threefold. First, we study the implications of process virtualization in the context of telehealth. Specifically, we unveil the impact of *telehealth use* on healthcare utilization with a focus on two outcomes of outpatient care: (a) the number of outpatient visits and (b) total visit costs. Second, we reveal how telehealth achieves process virtualization by drawing on the lens of Process Virtualization Theory

(PVT). Since telehealth represents a specific instance of process virtualization, we focus on three dimensions - reach, representation, and monitoring - to explain the underlying mechanisms that enable process virtualization of specific disease types (Overby 2008). We argue that the interplay between disease types and information technology (IT) capabilities, can impact the degree of process virtualization. Third, we analyze the *differential* impact of telehealth based on the virtualizability of different disease types. Unlike previous research that primarily focused on hospital-level, telehealth adoption or survey methods to assess the role of telehealth, we construct *granular measurements of actual telehealth use* for each patient visit by leveraging a unique patient dataset from Maryland. This allows us to measure the impact of telehealth on process virtualization at the patient level. Hence, our research addresses the call by Tuckson et al. (2017, p. 1587), who observed that "…. *enhanced evidence is required to address gaps in telehealth-related clinical performance* …."

Our findings indicate a significant reduction in healthcare utilization after telehealth use. Specifically, we observe a 13.6% reduction (or 0.15 visits) in the number of outpatient visits, equivalent to $239 in total cost reduction, within 30 days after provisioning telehealth. Our results reveal that these improvements can be attributed primarily to disease types with care processes that are more amenable to virtualization. Among patients with highly virtualizable diseases, we observe a 12.2% (or 0.21 visit) reduction in the number of future outpatient visits, equivalent to a cost reduction of $179.5 within 30 days. Our findings reveal a critical boundary condition related to telehealth use, i.e., *substitution effect* for patients with high virtualizability diseases using telehealth. We find empirical evidence supporting telehealth's representation and monitoring abilities that effectively reduce future healthcare utilization. Specifically, telehealth's ability to provide virtual representation through integration of sensory and relationship features for specific diseases, such as mental health, skin disorders, metabolic, and musculoskeletal diseases, significantly reduces future healthcare utilization. Furthermore, the ability to monitor patients and control disease progression due to telehealth's monitoring capability leads to displacement in the timing of healthcare utilization among chronic disease patients (Thompson et al. 2020). However, we do not observe a significant impact of telehealth's reach capability in reducing utilization, consistent with earlier findings on its lack of effectiveness in reaching patients who live farther away from the point of care (Chao et al. 2021, Yeow and Goh 2015). Our findings reveal essential tradeoffs in provisioning telehealth across disease types with respect to their virtualizability.

Our research provides several research and policy prescriptions. First, our study represents one of the first attempts to comprehensively analyze the economic impact of process virtualization in the context of telehealth. Second, we demonstrate the differential and nuanced impact of telehealth on resource utilization for distinct disease types, which varies based on their degree of virtualizability. Third, our research empirically tests the tenets of PVT and implies that not every aspect of technology addresses the requirements of process virtualization. In a telehealth context, advocates of virtualization should carefully analyze their contextual boundary conditions and resources, as IT cannot entirely reduce resistance to virtualization. However, our results provide evidence that telehealth can be highly effective in monitoring disease progression, thereby substituting in-person visits with lower care utilization and costs. Our findings are critical for policymakers to develop new reimbursement models and promote telehealth adoption for specific diseases and conditions, as a means to bend the cost curve and support the shift toward outpatient and home-based care services.

2 BACKGROUND

First, we provide a brief background of process virtualization and prior studies on telehealth and identify the critical research gaps in our understanding of the underlying mechanisms behind virtualization in healthcare.

2.1 Process Virtualization

The proliferation of digitization and need to serve clients across time and space have led organizations to migrate their processes to virtual environments (Overby et al. 2010). Process virtualization occurs when the physical interaction between people and objects is replaced by virtual interactions (Fiol and O'Connor 2005). For instance, patients can visit their doctors virtually through a telehealth platform, students can attend courses virtually from off-campus locations, and customers can use mobile devices to shop online without going in person to stores (Berguerand 2022, Sickler 2022, Weiler 2020). Although anecdotal evidence suggests that process virtualization substantially improves quality of life, improves access to untapped resources, and promotes a more engaged society, research in this area is still nascent. Understanding how to design and use virtual processes and the implications of transitioning to virtual processes are of great importance to practitioners and policy makers to maximize and democratize the potential benefits to society.

Prior studies in the IS literature have considered the antecedents and consequences of process virtualization in various contexts. For instance, Miscione (2007) examined the factors impacting telemedicine adoption in rural areas, while Piccoli et al. (2001) study virtualization of educational processes and reported similar learning outcomes compared to classroom settings. Bose and Luo (2011) identified the factors contributing to a firm's virtual green IT initiatives. Balci (2014) studied the impact of perceived process requirements on airline online check-in processes, while Graupner and Maedche (2015) found that sensory and control requirements are vital influencers of virtualization in online banking processes. Ofoeda et al. (2018) also showed that process requirements impact virtualization of government-to-citizen engagement processes.

Overby (2008) established the foundation of Process Virtualization Theory (PVT) to understand factors affecting the virtualizability of processes in several ways. First, PVT examines the characteristics of a process instead of solely focusing on outcomes, such as IT adoption. Second, PVT extends the contextual setting of media richness theory by involving person-to-object interactions. Third, PVT seeks to understand why a process may be amenable to virtualization. However, there remain several gaps in our understanding of how processes are virtualized, which tasks should be virtualized, whether users substitute or complement physical processes with virtualization, and whether the benefits of virtualization are equally realized across users and tasks. Our objective is to enrich our understanding of process virtualization using the context of telehealth use for patient care. We specifically focus on whether virtualization in healthcare can help improve outcomes (e.g., outpatient visits and costs), for which tasks (e.g., diseases) and under what conditions can virtualization achieve better results, and whether the proposed IT constructs (i.e., reach, representation, and monitoring) of PVT can help explain the underlying mechanisms of care virtualization processes.

2.2 Telehealth

Telehealth is defined as "the use of electronic information and telecommunication technologies to support long-distance clinical health care, patient and professional health-related education, health administration, and public health."[1] Telehealth enables such processes through electronic platforms either using proprietary vendor applications, such as American Well, MD Live, Teladoc, and integrated EHR applications (e.g., patient portals), or through general-purpose platforms, such as FaceTime, Skype, and Zoom.

In recent years, the U.S. government has provided incentives to create and expand providers' virtual consultation capabilities. The Federal Communications Commission (FCC) established a COVID-19 Telehealth Program with $200M in funding to help eligible healthcare providers deliver care to patients in a virtual setting.[2] In March 2020, the Centers for Medicare & Medicaid Services (CMS) broadened access to telehealth services through its CMS 1135 waiver so that beneficiaries could receive a wide range of services virtually without traveling to a healthcare facility (CMS.gov 2020). In our research context, we focus on telehealth visits where patients and providers communicate through a *synchronous* virtual video conferencing platform. This type of service represents the predominant form of virtual visits, accounting for 24% of all office visits and 35% of home health services (Bestsennyy et al. 2021).[3]

Although telehealth has existed for over two decades, the literature lacks empirical evidence to justify the economic and clinical impact of care virtualization through telehealth based on longitudinal analyses of a large patient population (Adler-Milstein et al. 2014). To highlight the current state of the telehealth literature, we present a comprehensive summary of the prior literature in Table A1 in the Appendix. In this comparative analysis, we consider the types of telehealth services (e-visit via video, phone, or message, tele-triage, telemonitoring, e-health, and patient portal use), use versus adoption, mode of telehealth (synchronous vs. asynchronous), outcomes, disease types, research method (empirical, modeling, or mixed-method), data context, study design (cross-section or panel), and the length of study.

We observe that earlier findings span a diverse range of studies, based on different types and modes of telehealth services and diseases, and provide mixed evidence. Some studies used small-sample data with short

[1] https://www.hrsa.gov/rural-health/topics/telehealth/what-is-telehealth, last accessed on 02/04/2023
[2] https://www.fcc.gov/covid-19-telehealth-program-invoices-reimbursements, last accessed 02/04/2023.
[3] Telehealth provides three types of IT-enabled capabilities: (a) real-time, two-way interaction between a patient and healthcare provider via audiovisual technologies; (b) store-and-forward systems that transmit patient health data, such as X-rays and radiology images, to healthcare providers and specialists; and (c) remote-monitoring capabilities involving collection and transmission of personal and medical patient data to healthcare providers at distant locations (AHA 2015).

observation periods or were based on a telehealth use at a single provider (Bakitas et al. 2020, Hwang et al. 2022, Kelley et al. 2011). Others used cross-sectional data only (Rodriguez et al. 2021, Weiner et al. 2021), while several studies evaluated pilot implementations (Miscione 2007, Paul and McDaniel 2004, Yeow and Goh 2015), or focused only on specific diseases (Bao et al. 2020, Erdogan et al. 2018, Goh et al. 2016, Li et al. 2021, Liu et al. 2018, Savoli et al. 2020). We also observe that many studies considered different types of telehealth other than synchronous virtual visits, such as online social support (Yan and Tan 2014), tele-radiology (Körpeoğlu et al. 2014), remote monitoring (Singh et al. 2011), tele-triage (Çakıcı and Mills 2021), and tele-cystoscopy (Erdogan et al. 2018). Our study represents one of the first attempts to focus on the most generic version of telehealth services - *e-visit via video* – supported by a strong theoretical framework based on the salient IT constructs in PVT, i.e., reach, representation, and monitoring capabilities of virtualization.

Our study examines the impact of care virtualization through telehealth at the patient-visit level, based on statewide longitudinal data of telehealth use, across a large patient population. Further, our study focuses on future healthcare utilization, based on the number of outpatient visits and total costs within the 30-days following a telehealth visit. This is a crucial distinction in terms of its ability to assess the actual economic value of common types of virtual care provisioning, as highlighted in the panel labeled "E-visit: Video" shown in the last row of Table A1. For example, prior studies have explored the impact of telehealth use on emergency department length of stay (Sun et al. 2020), service rate (Rajan et al. 2019), patient satisfaction (Li et al. 2020), diagnostics (Serrano and Karahanna 2016), healthcare process outputs (Yeow and Goh 2015), and the number of follow-up visits (Li et al. 2021). Most of these studies do not comprehensively capture the economic value of video-based, e-visits as the mode of care delivery.

2.3 Telehealth and PVT

Telehealth represents a specific instance of process virtualization in a healthcare setting. PVT lays the foundation to study "process virtualizability," which is defined as the amenability of a process to being conducted without the physical presence of actors and objects. PVT proposes four main constructs that influence process virtualizability: *sensory, relationship, synchronism, and identification and control* requirements (Apte and Mason 1995). These requirements can negatively impact process virtualizability by increasing resistance and creating friction for a process to be conducted virtually (Overby 2008). For instance, a clinical consultation involves information exchange between a patient and their provider for diagnosis and treatment. In a physical context, the four requirements are immediately satisfied, ascertaining an effective medical consultation process. However, these requirements are harder to satisfy in a virtual consultation setting since the relationship between a patient and their care provider is more difficult to establish (White et al. 2022), thereby lowering the likelihood of process virtualizability. However, the technological capabilities of telehealth enable greater process virtualization with low friction. Therefore, we expect that telehealth use is likely to substitute in-person visits and lower future healthcare utilization.

First, sensory requirements convey the level of fully equipped sensory experience needed to perform a process, such as tasting, seeing, hearing, smelling, touching, and emotions. In a healthcare context, for example, diagnosing heart murmurs in kids mostly requires physical examination using stethoscopes. Moving the process to a fully virtual environment is difficult because providers can only use two of their five senses—seeing and hearing. Second, PVT defines relationship requirements as the need for social or professional interaction among participants to build trust, friendship, and acquire knowledge. If a process requires higher relationship requirements, it will encounter more difficulty in transmitting a set of standard communication cues, such as gestures, posture, and inflection, if virtualized (White et al. 2022). Third, synchronism requirements pertain to the degree of alignment and bandwidth for smooth communication without delay. While synchronism can be readily established in a physical process, it is not straightforward in virtual processes since latency related to wait times can add friction to virtualization (Kamarainen and Punakivi 2004). Finally, identification and control requirements address the need for authentication of process participants and control over their behavior. This is because virtual processes suffer from identity spoofing and control problems, such as difficulty in influencing participant behavior or monitoring participants (Friedman and Resnick 2001). Overall, these requirements collectively influence the amenability of a business process toward virtualization.

So how can telehealth help to facilitate process virtualization? PVT conceptualizes IT as an enabler of virtualization by mitigating the resistance to process requirements through three IT capabilities: representation, reach, and monitoring (Overby 2008). *Representation* conveys telehealth's capability to represent relevant information via simulations of actors and objects, their properties, profiles, and characteristics as information moves from the physical into the virtual world. With representation, IT can integrate sensory and relationship requirements and reduces their negative impact on process virtualization. For instance, representations of patient symptoms and medical conditions can be conveyed through a telehealth consultation to a distant provider so that patients can be diagnosed virtually.

Reach is conceptualized as the capability to allow process execution across time and space, allowing a process with high relationship and synchronous requirements to be virtualized. Telehealth can expand geographic reach, thereby helping patients in rural settings access healthcare resources (Yeow and Goh 2015) and allow synchronous execution of medical counseling (Chao et al. 2021). Furthermore, telehealth can improve access to patients who may otherwise miss appointments due to long wait times for in-person visits (Osadchiy and Kc 2017).

Finally, the *monitoring capability* of IT serves as a mechanism to authenticate participants and track their activities and helps reduce resistance within processes that exhibit high identification and control requirements. For example, telemonitoring helps patients to improve their health status by virtually connecting them to providers, sharing medical assessments, and establishing virtual counseling to monitor disease progression (Singh et al. 2011). In this manner, IT can help mitigate the resistance to sensory, relationship, synchronism, and control requirements in healthcare.

3 THEORY FOUNDATION

In explaining how telehealth use changes healthcare utilization at a high level, our study builds on the theoretical underpinnings of *Process Virtualization Theory (PVT)*. We are interested specifically in (a) the boundary conditions under which virtualization of medical processes can be achieved, and (b) how telehealth-enabled virtualization can impact healthcare utilization. In this section, we will theorize and present our hypotheses based on the research questions identified in the introduction.

3.1 Telehealth and Healthcare Utilization

In the U.S., certain geographical areas suffer from a shortage of primary care physicians, specialists, and/or access to primary care (Gellis et al. 2014). Lack of access to outpatient clinics may delay preventive care, which can aggravate health conditions leading to a higher rate of future readmissions or ER visits (Kangovi and Grande 2011). However, Darkins et al. (2008) reported that veterans who joined home telehealth programs experienced a 25% drop in bed-days of care and a 19% reduction in hospital admissions. Similarly, Zhou et al. (2007) documented a 6.7% to 9.7% reduction in adult primary care outpatient visits among patients who adopted electronic messaging with their providers. Hence, we argue that telehealth plays an essential role in providing virtualized care and bridges the digital health divide due to its superior reach in connecting underserved patients to primary (or specialty) providers.

Telehealth also offers remote monitoring capabilities (through sensors and mobile diagnostic systems), patient education, and virtual visits with providers via phone or video calls (Dorsey and Topol 2016). For instance, virtual telemonitoring of obstetric patients with COVID-19 is an effective surveillance tool as telehealth provides close monitoring and enables a smoother transition to virtual evaluation (Krenitsky et al. 2020). Preventive home monitoring of patients with chronic obstructive pulmonary disease (COPD) exhibited reduced hospital admission rates (Dinesen et al. 2012). Hence, we posit that the monitoring capability of telehealth can help improve patient health status which, in turn, can lead to reductions in future utilization.

Research supports care virtualization in occupational therapy settings as therapists mainly use assessments and perform interventions through conversations with patients and their families (Cason 2014), supporting the efficacy of telehealth's representation capability. Similarly, telehealth use for mental disorders and substance abuse has proven to be a promising alternative to in-person consultations due to its ability to represent patient symptoms via teleconferencing and support for patient privacy considerations (Kinley et al. 2012). Telehealth has also been reported to improve relationship requirements as it can reduce burnout and stress among nursing staff by streamlining patient conversations and managing patient meetings more effectively (HIMSS TV 2020). Hence, telehealth can effectively manage sensory and relationship requirements of treatments through its representation capability.

We argue that telehealth can influence healthcare resource utilization by narrowing the digital health divide, fostering patient self-care management, and establishing communication between providers and patients (Bashshur et al. 2014). Hence, telehealth may reduce the need to seek future outpatient care, thereby resulting in lower utilization of clinical services. Hence, we hypothesize that,

H1: Patients who undergo telehealth visits are more likely to exhibit a reduction in their utilization of future outpatient services compared to patients who do not use telehealth.

3.2 Virtualizability across Disease Types

During clinical consultation, a patient's underlying health condition can determine the extent of process requirements and their interplay with IT capabilities. For instance, the adoption of mobile communication technologies by nurses is affected by the level of patient or disease identification and the availability of current information at the point of care (Junglas et al. 2009). Overby et al. (2010) argued that tasks, such as initial screening, can be good candidates for telemedicine, while other tasks, such as delivery of a negative diagnosis, might be poor candidates. Hence, we consider the degree of virtualizability of different disease types as a contextual factor and study the heterogeneous impact of disease types.

The four requirements of PVT are influenced by the characteristics of participants and disease types. While a preliminary conversation with providers may involve discussion of a patient's medical history, pre-existing conditions, allergies, and current medications, they carry low sensory, relationship, and control requirements, compared to in-person patient exams which may necessitate greater requirements depending on the disease. For example, diseases that require visual inspection or verbal communication, such as psychiatry, dermatology, and endocrinology, have lower sensory requirements, compared to diseases that necessitate physical examination for diagnoses (e.g., appendicitis, heart murmur, arthritis, and arthralgia). Hence, disease types and care requirements are likely to impact the virtualizability of care processes.

High virtualizability diseases tend to exhibit lower resistance to virtualization since these diseases are better suited to telehealth's reach, representation, and monitoring capabilities. For instance, mental health patients require regular follow-up care and monitoring to monitor disease progression (Anker et al. 2011, Wakefield et al. 2008). Although mental health illnesses may have greater synchronism and control requirements, these may be offset by proper use of telehealth's monitoring and reach capabilities. Prior research has reported that telepsychiatry patients experience 50% lower depression scores and significantly fewer ER visits after reinforced self-efficacy and depression counseling through telehealth (Gellis et al. 2014).

On the other hand, telehealth use among patients with other types of diseases may serve as a gateway to future offline or in-person clinic visits due to the limitations imposed by their process requirements (Bavafa et al. 2018). Some diseases progress rapidly and are accompanied by distinct symptoms that require urgent care. For instance, appendicitis, heart arrhythmia, and abnormal uterine bleeding may require in-person physical examination because granular patient information processing under high sensory requirements cannot be sufficiently conveyed through telehealth. For instance, Palen et al. (2012) observed that inpatient hospitalizations and ER visits among patients with low virtualizability diseases increased by 38% and 7%, respectively, following the adoption of secure electronic communication with providers.

In this research, we analyze the differential impact of virtual care processes associated with high and low virtualizability diseases. Since low virtualizability diseases typically require substantial interventions for which telehealth may not be suitable, telehealth may instead serve as a gateway to in-person care (Bavafa et al. 2018). However, for patients with diseases with high virtualization potential, such obstacles can be better handled through the representation, reach, and monitoring capabilities offered by telehealth. Therefore, we expect telehealth to reduce utilization more among patients with high virtualizability diseases compared to those with low virtualizability diseases.

H2: Patients who use telehealth for high virtualizability diseases are more likely to exhibit future reduction in healthcare utilization compared to patients who use telehealth for low virtualizability diseases.

3.3 Telehealth Capability and Process Virtualization

Telehealth's efficacy relies on the quality of telecommunication infrastructure and the extent to which it fulfills the requirements of process virtualization. In this respect, telehealth's greater representation, reach, and monitoring capabilities can be more conducive to virtualize the treatment of high virtualizability diseases. In other words, the relationship between disease type and telehealth's capabilities (i.e., representation, reach, and monitoring) can impact the degree of digitization and process virtualization. High virtualizability diseases generally exhibit well-established and standardized protocols based on clinical knowledge. Such diseases exhibit low sensory requirements and include behavioral interventions such as promoting healthy eating, exercise, meditation, smoking, and alcohol cessation counseling (Evert et al. 2013).

Similarly, the representation capabilities offered by telehealth are more conducive for diseases with low sensory requirements. For instance, telehealth has shown promising results in Australia and the U.S., where doctors use tele-dermatology to connect with distant patients and provide specialized diagnosis, representing an effective and safe approach to virtual treatments (Yeroushalmi et al. 2021). For neuromuscular and musculoskeletal diseases, telehealth can reduce the sensory requirements with the help of a telepresenter, who follows a specialist's directives during virtual physical exams, highlighting the role of telehealth's representation capability (Howard and Kaufman 2018). Furthermore, telehealth's reach can improve the lack of access to healthcare resources for rural patients and enable synchronous medical counseling (Chao et al. 2021, Yeow and Goh 2015). Hence, telehealth facilitates treatment of high virtualizability diseases more effectively through its reach, representation, and monitoring capabilities, which in turn helps reduce the need for future visits. We posit that telehealth's reach, representation, and monitoring capabilities facilitate virtualization of care processes resulting in a reduction in care utilization for high virtualizability diseases.[4]

H3: For patients with high virtualizability diseases, telehealth's representation, reach, and monitoring capabilities facilitate the virtualization of care delivery, leading to a reduction in healthcare utilization.

[4] We do not hypothesize a similar relationship for low virtualizability diseases as it is not meaningful to test the effect of telehealth on care delivery processes with low potential for virtualization.

4 RESEARCH DATA

We obtained our research dataset from the Maryland Health Services Cost Review Commission (HSCRC) outpatient records, which spans the period from Q4 of 2012 to Q1 of 2021. Maryland HSCRC tracks complete patient-level claims data, for *all hospital outpatient clinic visits* across the state of Maryland, with details of clinical and demographic information.[5] The data contains patient visit-level records across all 58 non-Federal hospitals in Maryland. Each patient is provided a unique patient identifier that follows patients over time and across all hospitals/clinics in the region and study their entire visit and diagnosis history.

On a typical telehealth visit, patients connect with providers through a secure videoconferencing telehealth platform. This provision of care, based on two-way, interactive videoconferencing from a provider site to the patient location, is defined as a telehealth visit or encounter (Nelson and Patton 2016). To identify telehealth visits, we followed the guidelines provided by CMS and HSCRC Data Analytics Center and used the CMS Current Procedural Terminology (CPT) modifiers GT and 95.[6] We identified 26,948 patients with at least one telehealth visit. As described in the next section, we matched these patients to patients who did not undergo any telehealth visit using propensity score matching (PSM). Our PSM approach resulted in 80,842 patients with no telehealth visits, for an overall total of 2,874,463 visits between 2012 and 2021.[7]

Table 1 reports the descriptive statistics of our model variables. The two dependent variables represent the *number of outpatient visits* and *total outpatient costs*, within 30 days after a telehealth visit. We used a 30-day time window to capture the effect of telehealth use on patients' short-term healthcare utilization, after a telehealth visit.[8] We created two dependent variables - *Visit30D* and *Cost30D* – which measure the number of outpatient visits and total costs incurred by outpatients, respectively, within 30 days after a telehealth visit.[9] In

[5] Maryland state law requires all hospitals to submit their claim records to the HSCRC for cost review purposes. Hence, we followed HSCRC directions to identify telehealth visits. https://hscrc.maryland.gov/Pages/default.aspx, last accessed 02/04/2023.
[6] For telehealth procedure identification, we followed the coding approach suggested by HSCRC as it takes into consideration the approach adopted by Medicare, Maryland Medicaid, and private payers in Maryland.
[7] To isolate the possible effect of the COVID-19 pandemic that started in 2020, we also performed a robustness test by focusing only on the time period before 2020 and observed consistent results.
[8] We also extended our analysis to a 90-day window in our robustness checks and observed consistent results.
[9] We used the hospital cost-to-charge ratio to calculate the actual costs incurred.

calculating future utilization, we followed the medical literature and only considered future visits with the same principal diagnoses as the index visit (Bonafede et al. 2018, Stahl et al. 2015).[10] Accordingly, our dataset reveals an average of 1.1 visits (*Visit30D)* and outpatient costs of $888.40 (*Cost30D*) within 30 days. We observed an average incidence of 3.4% telehealth visits among all visits.

Table 1. Descriptive Statistics

Variable	**Variable Definition**	**Dimension**	**Mean**	**Std. Dev**
Visit30D	Number of visits within 30 days (of focal visit)	Continuous	1.10	3.25
Cost30D	Dollar value of total cost within 30 days (of focal visit)	Continuous	888.94	3624.79
Telehealth	Binary (1 = if visit involves at least one telehealth proc)	0 or 1	0.03	0.18
ChronicVisit	Binary (1 = if Principal Diagnoses is chronic)	0 or 1	0.67	0.47
Num_Comorbidities	Total number of patient comorbidities	Continuous	0.39	0.66
PastVisit365D	Number of past visits within 365 days (of focal visit)	Continuous	7.91	20.27
%PastPCPVisit365D	Past PCP visits as a percent of number of past visits within 365 days	Continuous	19.9%	40.3%
%PastEDVisit365D	Past ED visits as a percent of number of past visits within 365 days	Continuous	2.4%	15.9%
RVU	Relative value unit	Continuous	1.63	2.27
PtAge	Patient Age	Continuous	41.43	21.41
PtSingle	Binary (1 = if Patient Marital Status: Single)	0 or 1	0.61	0.49
PtMarried	Binary (1 = if Patient Marital Status: Married)	0 or 1	0.26	0.44
PtMariStatOther	Binary (1 = if Patient Marital Status: Other)	0 or 1	0.13	0.33
PtFemale	Binary (1 = if Patient Gender: Female)	0 or 1	0.62	0.49
PtBlack	Binary (1 = if Patient Race: Black)	0 or 1	0.49	0.50
PtWhite	Binary (1 = if Patient Race: White)	0 or 1	0.43	0.49
PtRaceOther	Binary (1 = if Patient Race: Other)	0 or 1	0.08	0.27
InsSelfPay	Binary (1 = if PayerDesc: Self Pay)	0 or 1	0.01	0.12
InsMedicare	Binary (1 = if PayerDesc: Medicare)	0 or 1	0.26	0.44
InsMedicaid	Binary (1 = if PayerDesc: Medicaid)	0 or 1	0.39	0.49
InsPrivate	Binary (1 = if PayerDesc: Private)	0 or 1	0.31	0.46
InsOther	Binary (1 = if PayerDesc: Other)	0 or 1	0.03	0.16

We account for the effect of several control variables involving time-variant patient and visit characteristics. First, we control for payer (insurance) types that may influence patients' healthcare utilization as insurance status has been observed to be one of the determinants of healthcare service utilization (Blackwell et al. 2009). For each patient visit, payer type is categorized into one of five insurance classes: Self-pay (1%), Medicare (26%), Medicaid (39%), Private (31%) and Other (3%). Second, chronic disease patients may exhibit higher levels of healthcare resource consumption as their perceived healthcare service needs may be elevated (Blackwell et al. 2009). Following ICD-9-CM and ICD-10-CM coding schemes developed by the Healthcare

[10] Healthcare utilization is defined as (i) the number of billable encounters in a year where a billable encounter is defined as a face-to-face contact between a patient and health professional whose services are covered by an insurance provider (Stahl et al. 2015), and (ii) direct costs incurred during a 12-month period which include gross covered payments for all healthcare services (Bonafede et al. 2018).

Cost and Utilization Project, we create a chronic disease indicator, *ChronicVisit*, and deploy it as a control variable in our analysis. We observe that 67% of visits are related to chronic disease care.

Next, we control for the *number of comorbidities* present at the time of a patient visit as a proxy for patient severity, following the Charlson Comorbidity Index calculation developed by Quan et al. (2005). To isolate a patient's health-seeking behavior, we control for the number of past visits within the last one year of a focal visit, *PastVisit365D* (Clewley et al. 2018). We also include the percentage of past primary care provider (PCP) visits, *%PastPCPVisit365D*, and emergency department (ED) visits within the last year of the focal visit, *%PastEDVisit365D*, to further account for factors that may impact patients' telehealth decisions and their future healthcare utilization (Clewley et al. 2018). On average, we observe 7.9 outpatient visits within the last year of a focal visit, of which 19.9% are PCP and 2.4% are ED visits. To control for challenges associated with financial compensation of telehealth services, we include the work relative value unit (RVU) metric of each visit (Weigel et al. 2020). RVUs are used by Medicare to determine payments to providers and serve as a proxy for physician compensation and productivity (BDO 2020). We also control for predisposing characteristics that may determine utilization of healthcare resources (Blackwell et al. 2009), including patient age (*PtAge*) and marital status (*PtSingle*, *PtMarried*, or *PtOther*).

5 METHODOLOGY

Our econometric estimation examines the impact of telehealth use on the utilization of healthcare resources, using panel data analysis. In doing so, we include several controls and fixed effects to account for time-variant and time-invariant effects in our model. We specify a generalized version of the multivariate model with patient and time fixed effects, as shown in equation (1).

$$Utilization_{iht+1} = \beta_1 Telehealth_{iht} + \boldsymbol{\beta} \cdot Controls_{iht} + \theta_i + \varphi_h + \lambda_t + \epsilon_{iht} \quad (1)$$

where *i* indicates the patient, *h* indexes an outpatient clinic (hospital), and *t* refers to the time of visit. We control for patient fixed effects with θ_i, outpatient clinic fixed effects with φ_h and time (quarter) fixed effects with λ_t. We estimate equation (1) for *Visit30D* and *Cost30D* as the *Utilization* variable. In the controls vector, we include a chronic visit identifier and patients' time varying covariates - age, marital status, insurance type, number of comorbidities, and RVU of the visit. We also control for the *number of past patient visits* that occurred in the year prior to the current visit at time *t*, percent of past visits that are PCP visits, and percent of visits that are ED visits. Doing so accounts for time-variant, systematic differences among patients who use healthcare resources at varying levels in the future. We also include the *number of comorbidities* to account for time-variant differences in a patient's health status that may change during our observation period. The coefficient β_1 is of primary interest since it measures future changes in utilization for telehealth visits compared to in-person visits.

Although the controls in the fixed-effects model address concerns related to unobserved patient and visit-level (time-invariant) heterogeneity that may influence patients' decisions to use telehealth and utilize healthcare resources, identification of the impact of telehealth may still suffer from bias due to patient-specific, uncontrolled (time-variant) confounding factors exhibited by pretreatment control variables. Specifically, patients who do not use telehealth may differ systematically from those who use telehealth in terms of the distribution of the observed covariates, and hence, may not serve as representative counterfactuals (Rubin 2001). To tackle this problem, we followed a two-step identification strategy that (a) first matches patients using propensity score matching (PSM), and (b) then uses an instrumental variable (IV) approach to account for time-varying, visit-level, unobserved factors related to telehealth visits.

In the first stage, we classified patients into two groups - *telehealth* and *non-telehealth* - and assigned a patient to the *telehealth* group if she had a telehealth visit. To identity the *non-telehealth* group, we identified patients who did not receive any telehealth service but had similar characteristics to those patients who received telehealth. We used a one-to-many, greedy nearest-neighbor matching algorithm to locate and match three control patients for every treated patient (Rosenbaum 1989), because the number of patients with at least one telehealth visit was considerably lower than those without a telehealth visit. To implement the matching algorithm, we included several patient- and visit-level controls, including *chronic disease condition, age, race, marital status, gender,* and *number of past visits within a year* as matching covariates. This strategy resulted in a final dataset of 107,790 patients, comprising a total of 2,874,463 visits.

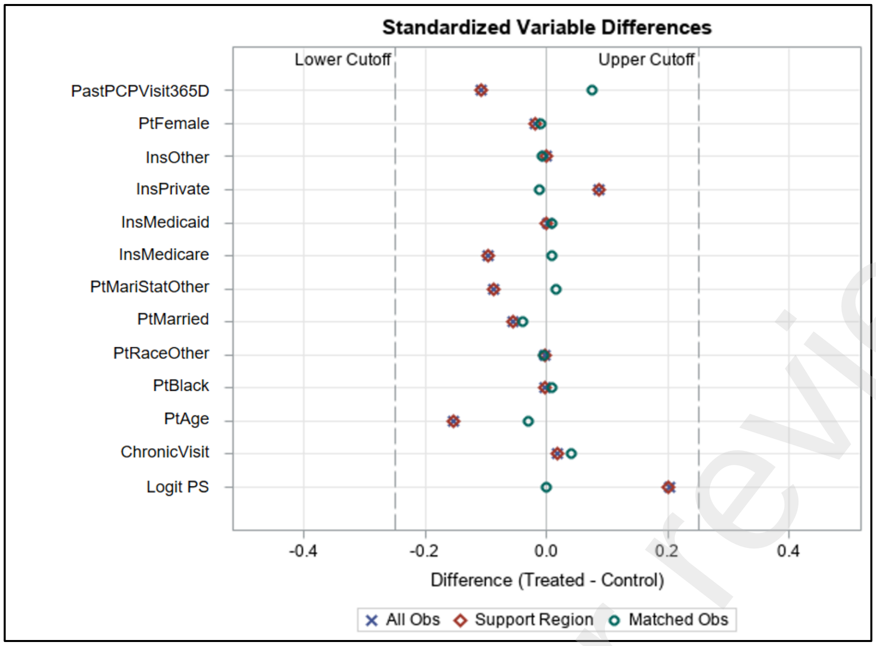

Figure 1. PSM Variable Statistics Before and After Matching

Our treatment group consists of 26,948 patients who underwent at least one telehealth visit, while the matched set of 80,842 patients without telehealth comprises the control group. On average, telehealth use was 3.4% across all the visits. Figure 1 shows the standardized mean covariate differences between treatment (patients with telehealth) and control (patients without telehealth) groups, before and after PSM. We observe that the logit propensity score between treatment and control groups reduced from 0.201 to -0.0001, and the absolute standardized mean differences for all matching variables are less than the recommended upper limit of 0.25 (Rubin 2001).

5.1 Instrumental Variable Approach

Although we account for confounding time-invariant effects and pre-treatment, patient-level confounding factors through matching, telehealth use may still suffer from endogeneity due to uncontrolled visit-level confounding factors that may be time variant. For instance, patients who live in rural areas may be more inclined to use telehealth compared to patients in urban areas, due to disparities in access to healthcare resources. To address such endogeneity concerns, we applied an IV estimation approach.

Any potential IV candidates should explain the variations in our endogenous variable, *Telehealth*, while not being systematically co-determined with the dependent variables of interest—*Visit30D* and *Cost30D*. One such possible IV is a patient's physical distance to the focal hospital/clinic that served as the originating site for the telehealth visit *relative to* the distance from the nearest hospital (to the patient's residence) where the patient could have received treatment from. Hence, we measure *DiffDistance* as the difference between (a) the distance from a patient's home zip code to the focal hospital, and (b) distance from the patient's home zip code to the closest hospital, measured in miles. First, the physical distance between a patient's home location and the hospital can be considered as a proxy for socio-economic conditions in areas with little or no access to healthcare (Bavafa et al. 2018). Such patients need to travel farther to access healthcare services and are more likely to utilize telehealth (Rajan et al. 2019). In contrast, the raw distance to the hospital may impact future utilization, which does not fulfill the exogeneity condition of an IV (Nemet and Bailey 2000).

To eliminate this plausibility, we introduce a *relative distance* metric where we address the possibility of having nearby options. Our relative distance metric, *DiffDistance*, is the difference between the distance to the focal hospital (where treatment is received either in-person or virtually) and distance to the nearest hospital from a patient's residence (see Figure 2). Higher values of *DiffDistance* indicate that the patient is likely to travel farther from the nearest hospital to receive care and, are therefore, more likely to use telehealth. Similarly, patients who do not avail services at the nearest hospital may indicate a lack of appropriate resources or access. Furthermore, higher values of *DiffDistance* do not necessarily mean that the patient's future healthcare utilization will be low, since non-negative values of this metric implies that there are alternative hospitals where the patient can choose to be treated. On the other hand, it is reasonable to assume that the distance from a patient's residence to the focal hospital (relative to the nearest hospital) is exogenous to the healthcare outcomes of interest, since their choice of residence is likely to be guided by other exogenous factors (e.g., school district, family income) but unlikely to be determined by future health outcomes.[11]

[11] We also checked a version where we divided *DiffDistance* by the distance to the nearest hospital to address scaling issues. Scaling the distance metric yielded similar results.

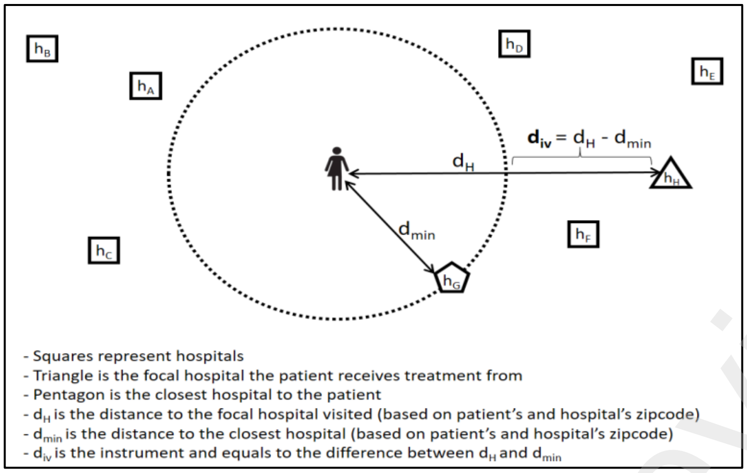

Figure 2. Visualization of *the DiffDistance* Instrument Construction

We conducted several tests to ensure the quality of our IV selection. First, the Hausman test, which compares OLS with 2SLS estimates, rejects the absence of endogeneity in the *telehealth* variable with a p-value of 0.006. Second, we checked whether the IV, *DiffDistance*, satisfies the relevance property of IV in 2SLS. We employed a weak identification test of the IVs, using a Kleibergen-Paap Wald rank weak instruments test, where the null hypothesis suggests that the model is underidentified or the instruments are weak. The Kleibergen-Paap rank Wald F statistic is 74.109, which is above the 10% maximal Stock-Yogo critical value, suggesting that the maximum bias in our IV approach can be at most 10% of the bias in an OLS approach. Hence, we conclude that our IVs are not weak and meet the necessary criteria for selection. We also perform falsification tests to assess the exogeneity of our IV in Section 6.4.6.

When the endogenous variable is binary, a standard 2SLS approach may yield inconsistent estimates (referred to as forbidden regression), since the fitted values of a binary variable from the first stage estimation will not be binary, nor will they be probabilistic in the second stage (Wooldridge 2010). Therefore, as suggested, we adopt a three-step approach where we first estimated a Probit model and regressed *Telehealth* on our instrumental variable and other controls, including patient, hospital, and time fixed effects (Angrist and Pischke 2008). In the second step, we calculate the predicted values of *Telehealth* from the first stage, which we denote as *Telehealth_hat*. In the third step, we follow a regular 2SLS estimation approach with

Telehealth_hat being the only IV for the endogenous *Telehealth* variable. This estimation produces consistent and unbiased estimates (Angrist and Pischke 2008). We provide the first stage results in Appendix Table A2.

To further alleviate concerns related to instrument selection, we explored two alternate potential instruments. First, the extent of *broadband Internet penetration* in the market area of a hospital may serve as an alternative instrument.[12] Having broadband access is a prerequisite for telehealth, since it is difficult to conduct telehealth visits without broadband Internet service. However, availability of broadband in a hospital's service region is unlikely to be *directly* correlated with the number of patient visits or visit costs, since these measures are driven by patients' underlying health conditions. We define the market area of a hospital as its Hospital Service Area (HSA) based on the Dartmouth Atlas of Health Care.[13] We calculated the HSA level broadband Internet penetration and included it as an instrument in our 3-step IV approach. We report our results and IV statistics in Appendix Table A3 (column 1) and observe qualitatively consistent results.

Another alternative IV is the level of telehealth use by patients in their neighboring zip codes (Angst et al. 2010, Ganju et al. 2022). This is because the focal patient's telehealth decision may be correlated with other patients' telehealth use in neighboring zip codes due to similarities in service availability and access to care, but the telehealth use of other patients should not directly affect the focal patient's future healthcare utilization. Accordingly, we calculate the telehealth use in a patient's neighboring zip codes in the same year-quarter and used it as an alternative instrument in our estimations. The estimated coefficients of telehealth use for future visits and costs following a 3-step IV approach are reported in Appendix Table A3 (column 2). Overall, we observe that the sign and significance of our results are similar for both alternate instrumental variables.

[12] We obtained high speed Internet connection data from Form 477 Census Tract Data on Internet Access Services provided by Federal Communications Commision. We considered the highest speed connection available in both directions (download and upload) during our study period. https://www.fcc.gov/form-477-census-tract-data-internet-access-services, last accessed 02/04/2023

[13] https://data.dartmouthatlas.org/supplemental/#boundaries, last accessed 02/04/2023.

6 RESULTS

6.1 Effect of Telehealth on Healthcare Utilization

Our IV estimation results are reported in Table 2. Accordingly, if a patient has a telehealth visit, the total number of future outpatient visits decreased by 13.6% (β_1 = -0.147; $p < 0.01$) or 0.15 visit (=1.1*0.136) within the next 30 days, while total outpatient costs decrease by 26.9% (β_1 = -0.313; $p < 0.01$) or $239 (=888.9*0.269).[14] Our results support H1 and represent a significant finding with respect to the impact of telehealth on future utilization.

Table 2. Baseline Estimation Results for Healthcare Utilization

DV	Ln(Visit30D)		Ln(Cost30D)	
Telehealth	-0.147***	(0.004)	-0.313***	(0.022)
Ln(PtAge)	0.021***	(0.001)	0.081***	(0.020)
$Ln(PtAge)^2$	-0.010***	(0.001)	-0.028***	(0.006)
PtMarried	-0.008***	(0.002)	-0.011	(0.009)
PtOther	0.007***	(0.002)	-0.004	(0.009)
InsMedicare	-0.107***	(0.003)	0.060***	(0.013)
InsMedicaid	0.047***	(0.002)	0.237***	(0.011)
InsPrivate	-0.016***	(0.002)	0.235***	(0.015)
InsOther	0.104***	(0.003)	0.412***	(0.018)
Chronic	0.081***	(0.001)	0.776***	(0.003)
Num_Comorbidities	-0.015***	(0.000)	-0.106***	(0.003)
Ln(PastVisit365D)	0.167***	(0.000)	0.932***	(0.002)
%PastPCPVisit365D	-0.143***	(0.001)	-0.424***	(0.005)
%PastEDVisit365D	-0.089***	(0.001)	-0.257***	(0.011)
Ln(RVU)	-0.023***	(0.001)	0.009***	(0.003)
Patient Fixed Effect	Included		Included	
Hospital Fixed Effect	Included		Included	
Quarter Fixed Effect	Included		Included	
Observations	2,869,541		2,869,541	
R^2	0.158		0.149	

Bootstrap (n=50) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Regression results are based on 3-step IV estimation.

6.2 Disease Types and Care Virtualizability

We conducted an extensive literature review to study the degree of virtualizability of common diseases and summarize our findings in Appendix Table A4. Drawing on prior empirical evidence, we identified 16 disease groups based on their level of virtualizability on a scale of low, medium, and high. To further

[14] As our dependent variable is log transformed in the model, we calculate the effect size (in percentages) with the formula (exp(β)-1)*100 for one unit increase in the independent variable.

understand and confirm the types of diseases that are more amenable to virtualization using telehealth, we consulted 16 medical practitioners with experience in using telehealth, of whom 12 were affiliated with a leading academic medical center in the U.S. Using a survey questionnaire, we asked practitioners whether telehealth can virtualize care for each of the 16 disease groups based on HCUP's clinical classification software (CCS) guidelines (HCUP 2016). Practitioners were asked to score the disease categories based on three types of telehealth capabilities (i.e., reach, representation, and monitoring) to virtualize patient diagnosis and care (using a scoring scheme of 3 for likely, 2 for neither, and 1 for unlikely). We averaged the response scores for each combination of disease category and telehealth capability. We then classified their responses as high when the average score was more than the sample's average score plus 0.5 standard deviation. After obtaining a high versus low classification for each combination of disease and telehealth capability, we identified diseases in high virtualizability category if at least two of three dimensions were rated as high. We report the final classification of diseases based on their virtualizability in Table A5 of the Appendix.

We classified four disease categories in the high virtualizability category: (1) endocrine, nutritional, and metabolic diseases, (2) mental illnesses, (3) diseases of the skin and subcutaneous tissue, and (4) diseases of the musculoskeletal system. This classification is consistent with our theoretical arguments and prior evidence based on an extensive review of the telehealth literature, as shown in Table A4 of the Appendix. The remaining disease categories were classified as having low virtualization potential. Overall, the survey data collected from practitioners helped us identify the disease categories that are more amenable to virtualization, and thereby, distinguish high versus low virtualizability diseases. Next, our aim is to assess whether telehealth is more effective in reducing healthcare utilization among high virtualizability diseases, compared to low virtualizability diseases.

Table 3 reports the results of split-sample analyses based on the level of disease virtualizability. We observe that diseases with high virtualization potential exhibit significant reduction in future outpatient visits (*Visit30D*) and costs (*Cost30D*) after telehealth encounters. Specifically, when a visit is associated with a highly virtualizable disease, the total number of future visits decreases by 12.2% (β_1 = -0.103; p-value < 0.01) or equivalently 0.21 visits (=1.71*0.122), with a total outpatient cost reduction of 26.4% (β_1 = -0.307; p-value < 0.01) or equivalently $179.5 (=680*0.264), within 30 days after a telehealth visit. For low virtualizability diseases, however, we do not observe a significant impact of telehealth on future visits (β = 0.002; p-value > 0.10), but there is a marginally negative effect on total outpatient costs (β = -0.170; p-value < 0.10).

Table 3. Healthcare Utilization for Disease Categories with Low and High Virtualization Potential

DV	Ln(Visit30D)				Ln(Cost30D)			
	Low Virtualization		High Virtualization		Low Virtualization		High Virtualization	
Telehealth	0.002	(0.013)	-0.103***	(0.005)	-0.170*	(0.093)	-0.307***	(0.027)
Ln(PtAge)	-0.037***	(0.004)	-0.107***	(0.011)	-0.217***	(0.029)	-0.331***	(0.062)
$Ln(PtAge)^2$	0.009***	(0.001)	-0.002	(0.003)	0.058***	(0.010)	-0.007	(0.014)
PtMarried	-0.004*	(0.002)	-0.025***	(0.003)	0.014	(0.017)	-0.064***	(0.019)
PtOther	0.002	(0.002)	0.022***	(0.003)	0.005	(0.016)	0.036**	(0.016)
InsMedicare	-0.023***	(0.004)	-0.172***	(0.005)	0.063**	(0.025)	-0.023	(0.022)
InsMedicaid	0.021***	(0.003)	0.058***	(0.005)	0.237***	(0.020)	0.178***	(0.020)
InsPrivate	-0.007**	(0.003)	-0.022***	(0.005)	0.203***	(0.022)	0.180***	(0.021)
InsOther	0.222***	(0.006)	0.044***	(0.006)	0.590***	(0.031)	0.236***	(0.026)
Chronic	0.054***	(0.001)	0.084***	(0.001)	0.547***	(0.006)	0.734***	(0.008)
Num_Comorbidities	0.000	(0.001)	-0.029***	(0.001)	0.004	(0.005)	-0.268***	(0.006)
Ln(PastVisit365D)	0.114***	(0.001)	0.122***	(0.001)	0.853***	(0.005)	0.600***	(0.003)
%PastPCPVisit365D	-0.070***	(0.001)	-0.121***	(0.001)	-0.251***	(0.008)	-0.388***	(0.007)
%PastEDVisit365D	-0.052***	(0.002)	-0.053***	(0.003)	-0.249***	(0.014)	-0.099***	(0.022)
Ln(RVU)	-0.002***	(0.001)	-0.074***	(0.001)	-0.008	(0.005)	-0.058***	(0.006)
Patient Fixed Effect	Included		Included		Included		Included	
Hospital Fixed Effect	Included		Included		Included		Included	
Quarter Fixed Effect	Included		Included		Included		Included	
Observations	1,191,347		1,236,438		1,191,347		1,236,438	
R^2	0.108		0.107		0.087		0.084	

Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Regression results are based on 3-step IV estimation.
Low virtualization disease categories include (1) Infectious and parasitic diseases, (2) Neoplasms, (3) Diseases of the blood and blood-forming organs, (4) Diseases of the nervous system and sense organs, (5) Diseases of the circulatory system, (6) Diseases of the respiratory system, (7) Diseases of the digestive system, (8) Diseases of the genitourinary system, (9) Complications of pregnancy, childbirth, (10) Congenital anomalies, (11) Certain conditions originating in the perinatal.
High virtualization disease categories include (1) Endocrine, nutritional, and metabolic diseases, (2) Mental illness, (3) Diseases of the skin and subcutaneous tissue, (4) Diseases of the musculoskeletal system.

Taken together, our results support H2 and underscore the differential impact of disease types on the relationship between telehealth use and healthcare utilization.[15] This finding lends support to our argument that certain disease types may benefit more from process virtualization, leading to a substitution of future in-person visits and utilization among high virtualizability diseases. In contrast, low virtualizability visits do not exhibit a

[15] Comparison of coefficients between high virtualization and low virtualization models show a significant Chow test with Chi-square (df=1) = 127.71 and p-value = 0.000.

substantial change in healthcare utilization. A possible reason is that low virtualizability diseases require immediate treatment or follow-up (such as cancer, heart failure, or pneumonia), and therefore, telehealth may serve as a gateway to future in-person visits or as a referral channel to specialist services.

6.3 Role of Telehealth Capabilities

To test H3, we conducted several analyses to examine the impact of telehealth's individual capabilities (representation, reach, and monitoring) on future resource utilization, based on four metrics - ED visits, PCP visits, non-PCP visits, and costs. With respect to its *representation* ability, we considered disease categories that were rated high on the representation dimension in Table A5 (i.e., *HighRepresent* = 1). Next, we selected diseases that were rated low across all three dimensions of telehealth's capabilities and classified them in the low representation category (i.e., *HighRepresent* = 0), since the excluded diseases may have high ratings for reach and monitoring that could confound the counterfactual.[16] After constructing the indicator variable, *HighRepresent*, we interact it with *Telehealth*, and perform our 3-step IV estimation. We report these interaction estimation results in Table 4.

Table 4. Impact of Telehealth and Representation on Resource Utilization

Variable:	Dependent Variable							
	Ln(EDVisit30D)		**Ln(PCPVisit30D)**		**Ln(NonPCPVisit30D)**		**Ln(Cost30D)**	
Telehealth	-0.005	(0.003)	-0.112^{***}	(0.009)	0.003	(0.014)	-0.663^{***}	(0.108)
HighRepresent	-0.002^{***}	(0.000)	-0.004^{***}	(0.000)	0.043^{***}	(0.001)	0.303^{***}	(0.005)
Telehealth*HighRepresent	**0.002**	**(0.003)**	$\mathbf{0.043^{***}}$	**(0.009)**	$\mathbf{-0.102^{***}}$	**(0.014)**	$\mathbf{0.231^{**}}$	**(0.103)**
Controls	Included		Included		Included		Included	
Patient, Hospital, and Quarter Fixed Effects	Included		Included		Included		Included	
Observations	1,952,761		1,952,761		1,952,761		1,952,761	
R^2	0.029		0.020		0.082		0.101	

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.
Each cell refers to the coefficient estimate of the respective variable in a specific regression.
Regression results are based on 3-step IV estimation. Full results are available upon request

When *representation* capability is high, the coefficient of *Telehealth x HighRepresent* indicates that patients who undergo telehealth are likely to experience more PCP visits in the future (coeff. = 0.043, p-val < 0.01), but fewer non-PCP (i.e., specialist) visits (coeff. = -0.102, p-val < 0.01). We also observe a slight

[16] We also performed a robustness check for the low representation group (i.e., HighRepresent = 0) and included the four lowest-rated disease categories to sharpen the distinction between high and low representation groups. We observed qualitatively consistent results.

increase in future costs for telehealth visits that exhibit high representation. To better understand the impact on costs, we visualize the cost trends of high versus low representation diseases with respect to telehealth versus non-telehealth visits, as shown in Figure B1 of the Appendix. We observe that when telehealth is used to treat patients with high representation diseases, the cost gap between telehealth and in-person visits narrows over time, while the gap remains relatively stable for low representation diseases. Our results reveal an intriguing aspect of telehealth. While telehealth use does not impact future ED visits, it can improve follow-up care through more frequent PCP visits and reduce the need to seek non-PCP (or specialist) services.

Next, we study the impact of telehealth's *monitoring* ability on the incidence of future ED, PCP, non-PCP visits, and treatment costs. To proxy monitoring ability, we specifically examine chronic diseases because they often require constant monitoring and management of disease progression (Bestsennyy et al. 2021). Telehealth can preempt deterioration of chronic conditions which, if not treated in a timely manner, may result in adverse ED visits (Gellis et al. 2014). Since the clinical protocols for managing chronic diseases are well established based on evidence-based care pathways, we expect that patients with chronic diseases, if managed virtually through telehealth, will exhibit fewer visits and lower costs in the future. We performed a split sample analysis based on high versus low virtualization diseases following our earlier classification. We then estimate the interaction effect of telehealth and chronic visits on future healthcare utilization, as reported in Table 5. The coefficients of the interaction term, *Telehealth x Chronic*, suggest that when telehealth is used to manage chronic diseases with high virtualizability, patients will experience fewer PCP (coeff. = -0.087), non-PCP visits (coeff. = -0.261), and lower costs (coeff. = -1.45). While low virtualization cases also show a reduction in PCP visits and costs, we do not observe a significant effect on non-PCP visits.

Third, we examined the impact of telehealth's *reach* ability on future healthcare utilization. We used patients' geographic location (i.e., rural versus urban) to indicate whether the reach capability of telehealth is leveraged when medical processes are virtualized for patients in rural areas who may lack equitable access to in-person healthcare. The telehealth literature has also used rural settings to identify a lack of access to healthcare resources and observed that telehealth enables synchronous execution of medical counseling, suggesting facilitation of virtualization via its greater reach (Chao et al. 2021, Yeow and Goh 2015). We followed the rural area definition of the Office of Management and Budget and categorized patients into rural or urban locations based on their residential zip codes.[17] We performed a similar split sample analysis where we estimated the interaction effect of telehealth and rural (patient) location on future utilization for high and low virtualization visits. Our results are shown in Table 6.

Table 5. Impact of Telehealth and Monitoring on Resource Utilization

	Dependent Variable:							
	Ln(EDVisit30D)		**Ln(PCPVisit30D)**		**Ln(NonPCPVisit30D)**		**Ln(Cost30D)**	
Panel A – High Virtualization								
Telehealth	0.008	(0.005)	0.014	(0.016)	0.198^{***}	(0.032)	1.091^{***}	(0.232)
Chronic	-0.000	(0.000)	0.034^{***}	(0.001)	0.035^{***}	(0.001)	0.750^{***}	(0.009)
Telehealth*Chronic	**-0.007**	**(0.005)**	**-0.087^{***}**	**(0.016)**	**-0.261^{***}**	**(0.032)**	**-1.450^{***}**	**(0.230)**
Controls	Included		Included		Included		Included	
Patient, Hospital, and Quarter Fixed Effects	Included		Included		Included		Included	
Observations	1,236,438		1,236,438		1,236,438		1,236,438	
R^2	0.020		0.012		0.061		0.064	
Panel B – Low Virtualization								
Telehealth	-0.005	(0.004)	0.132^{***}	(0.011)	-0.016	(0.015)	1.399^{***}	(0.156)
Chronic	0.001^{**}	(0.000)	0.026^{***}	(0.001)	0.018^{***}	(0.001)	0.563^{***}	(0.006)
Telehealth*Chronic	**-0.005**	**(0.004)**	**-0.203^{***}**	**(0.015)**	**0.029**	**(0.020)**	**-2.233^{***}**	**(0.176)**
Controls	Included		Included		Included		Included	
Patient, Hospital, and Quarter Fixed Effects	Included		Included		Included		Included	
Observations	1,191,347		1,191,347		1,191,347		1,191,347	
R^2	0.019		0.027		0.027		0.065	

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.
Each cell refers to the coefficient estimate of the respective variable in a specific regression.
Regression results are based on 3-step IV estimation. Full results are available upon request

We observe that rural patients undergoing telehealth for high virtualizability diseases exhibit a higher incidence of PCP and non-PCP visits but incur lower costs, within 30 days after a telehealth visit. This suggests that rural patients with diseases that are amenable to virtualization may use telehealth as a triage (or gateway), and thus, may experience more PCP and non-PCP visits after telehealth consultations. Our results corroborate earlier findings which report that distance still matters for telehealth use, exacerbating the digital divide and geographic healthcare disparities (Goh et al. 2016, Hwang et al. 2022). While we observe a

[17] https://www.hrsa.gov/rural-health/about-us/what-is-rural, last accessed on 02/04/2023.

marginal reduction in cost after telehealth, we do not find evidence that telehealth's reach ability reduces healthcare utilization among rural patients. Hence, we report partial support for H3.

Table 6. Impact of Telehealth and Reach on Resource Utilization

	Dependent Variable:							
	Ln(EDVisit30D)		Ln(PCPVisit30D)		Ln(NonPCPVisit30D)		Ln(Cost30D)	
Panel A – High Virtualization								
Telehealth	0.001	(0.001)	-0.068***	(0.002)	-0.049***	(0.004)	-0.307***	(0.027)
Rural	0.007**	(0.003)	0.003	(0.004)	-0.045***	(0.007)	-0.011	(0.055)
Telehealth*Rural	**-0.000**	**(0.004)**	**0.028***	**(0.015)**	**0.138*****	**(0.022)**	**-0.317***	**(0.178)**
Controls	Included		Included		Included		Included	
Patient, Hospital, and Quarter Fixed Effects	Included		Included		Included		Included	
Observations	1,236,438		1,236,438		1,236,438		1,236,438	
R^2	0.021		0.013		0.061		0.064	
Panel B – Low Virtualization								
Telehealth	-0.008***	(0.002)	-0.010	(0.008)	0.009	(0.011)	-0.123	(0.094)
Rural	0.002	(0.002)	-0.009**	(0.005)	0.006	(0.006)	-0.101**	(0.045)
Telehealth*Rural	**-0.008**	**(0.013)**	**-0.027**	**(0.035)**	**-0.114****	**(0.054)**	**-1.661*****	**(0.488)**
Controls	Included		Included		Included		Included	
Patient, Hospital, and Quarter Fixed Effects	Included		Included		Included		Included	
Observations	1,191,347		1,191,347		1,191,347		1,191,347	
R^2	0.019		0.028		0.027		0.065	

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.
Each cell refers to the coefficient estimate of the respective variable in a specific regression.
Regression results are based on 3-step IV estimation. Full results are available upon request

Our empirical analysis delineates the sources of overall reduction in healthcare utilization, which can be attributed to the representation and monitoring abilities of telehealth. Specifically, telehealth's ability to provide virtual representation through integration of sensory and relationship features for specific diseases can reduce future healthcare utilization. For instance, we observe that using telehealth to communicate patient symptoms and medical conditions for mental health, skin disorders, metabolic, and musculoskeletal diseases, is an effective approach to substitute in-person visits. Furthermore, the monitoring capability of telehealth leads to a displacement in healthcare utilization among chronic disease patients (Thompson et al. 2020). Hence, chronic patients are less likely to incur costly specialist and PCP visits in the future. Our findings reveal important trade-offs in provisioning telehealth across distinct disease types with respect to their virtualization potential.

6.4 Robustness Analyses

We performed several robustness checks to strengthen model identification and the robustness of our findings. First, we deployed *coarsened exact matching* (CEM) at the visit-level. Second, we performed non-parametric matching using a *causal forest* approach to demonstrate the consistency of our earlier results. Third, we used a *Heckman* approach to re-estimate the impact of telehealth use and address identification concerns. Fourth, we tested our main results using a *time window of 90 days* to study whether the impact of telehealth on healthcare utilization manifests over a longer time horizon. As a consistency check, we focused on the period before 2020 to rule out concerns related to telehealth use during the COVID-19 pandemic. Finally, we performed robustness and falsification checks to further validate the exogeneity of our IV and our results.

6.4.1 Coarsened Exact Matching Approach

Previously we deployed PSM at the patient-level. To enhance the matching robustness, we utilize CEM at the visit level by matching telehealth visits to non-telehealth visits. CEM is a non-parametric method based on stratification and requires no assumptions about the data generation process (Iacus et al. 2012). CEM can improve covariate imbalance across treatment and control groups and reduce model dependence and statistical bias compared to parametric matching techniques (Iacus et al. 2012).

Drawing on the matched patient sample generated using PSM, we applied CEM at the visit-level to reduce the imbalance in our data across telehealth and non-telehealth visits. To perform CEM, we used patient time-varying covariates, *age, insurance,* and *marital status*, along with other visit-level characteristics such as a *patient's past visits* to account for health seeking behavior. We also coarsened the numerical variables by binning them into categorical levels. We have summarized our CEM matching criteria in Table B1 of the Appendix. The CEM algorithm matched 96,291 telehealth visits to 1,107,939 non-telehealth visits. We also provide the variable imbalance statistics in Table B2 of the Appendix and observe substantial improvements in the mean differences of treatment and control groups before and after CEM. Since we performed one-to-many matching, the control observations need to be weighted to balance the sample. We used CEM weights calculated for each observation with respect to the size of their strata in our econometric estimations.

To evaluate the results of the CEM approach, we estimated the econometric model in equation (1), where we included the controls as well as patient, hospital, and time fixed effects. Our results are shown in Table B3 and indicate that telehealth use results in a drop in the total number of future outpatient visits by 23.4% ($\beta_1 = -0.267$; $p < 0.01$), while total outpatient costs decrease by 14.9% ($\beta_1 = -0.162$; $p < 0.01$), within the next 30-day period. The CEM results are qualitatively and quantitatively similar to our main findings.

6.4.2 Causal Forest Approach

In addition to CEM, we implemented a *causal forest* (CF) non-parametric approach. CF is an extension of random forests and is a popular technique in the field of causal machine learning, which combines econometrics and machine learning approaches to estimate heterogeneous causal effects (Athey and Imbens 2016). Unlike traditional machine learning, where the goal is to minimize prediction error, CF aims to split data into subgroups (or leaves) in which the average difference in outcomes between treatment and control observations differs the most. With this goal, CF estimates the heterogeneous treatment effect across the entire sample by building thousands of individual trees through bootstrapping (Athey et al. 2019).

We applied this approach to examine the causal effect of telehealth use on future visits and outpatient costs. We include *time effects* (year-quarter identifiers) and *hospital identifiers* to account for time and hospital specific differences between telehealth and non-telehealth visits, as well as other patient controls. We used the *grf* package in R to estimate the causal forest. Using the entire sample, we generated 1,000 trees. To evaluate the CF results, we calculated the sample overlap-weighted average treatment effect (ATE) as the treatment propensities were very close to 0 or 1 (Li et al. 2018). The weighted ATE estimate for *Visit30D* is -0.077 (p-val < 0.01) indicating a reduction of 7.4% in the number of future visits for patients who underwent a telehealth visit, while the weighted ATE estimate for *Cost30D* is -0.080 (p-val < 0.01) indicating a reduction of 7.7% in future outpatient costs for patients with at least one telehealth visit.

6.4.3 Heckman Selection

Next, we address a potential selection issue in our telehealth use variable that may be attributed to unobserved latent selection of patients. We used a two-step Heckman selection procedure and estimated the inverse Mills ratio (*IMR*) from the first-stage probit model (Heckman 1979). First, we regressed *Telehealth* on all exogenous variables in our main model. We also included *DiffDistance* in the first stage as an exclusion restriction criterion for the second-stage regression since IMR is prone to collinearity, leading to incorrect standard errors in the second stage (Leung and Yu 1996). We then calculated the generalized *IMR* in a full treatment model, where $IMR = \phi(X_2\hat{\beta}_2)/\Phi(X_2\hat{\beta}_2)$ if $Telehealth = 1$ and $IMR = -\phi(X_2\hat{\beta}_2)/(1-\Phi(X_2\hat{\beta}_2))$ if $Telehealth = 0.$[18] Inclusion of the IMR in second stage panel estimation (with patient, hospital, and quarter fixed effects) as a control variable accounts for endogeneity concerns regarding patients' self-selection into telehealth visits (Wooldridge 2010). We report the second stage results in Table B4 of Appendix B, which indicate that patients with telehealth encounters experienced a 11.4% drop in the number of outpatient visits or a decrease of 0.13 visits ($p < 0.01$) in the subsequent 30-day period. Further, patients lowered their outpatient costs by 20.5% or $182 after a telehealth visit. Both results are consistent with our main findings.

6.4.4 Ninety-day Time Window

In the event that the impact of telehealth use on utilization persists or dissipates over a longer period, our earlier findings based on a 30-day time window may provide a partial estimate of its impact. Therefore, we extended our analysis to a window of 90 days and reported these results in Table B5 of Appendix B. We observe a significant decrease in the total number of outpatient visits following a telehealth visit, specifically a decrease of 0.6 visits (20.7%) and $951.6 in total costs (46.4%), in the subsequent 90-day period.[19]

6.4.5 Pre-Covid-19 Analysis

Our analysis of the impact of telehealth may be confounded by the COVID-19 pandemic, when telehealth use skyrocketed due to the pandemic lockdown. To alleviate this concern, we performed a robustness analysis by focusing only on the period before 2020. Accordingly, we performed PSM on the subset of visits that occurred before 2020. Our PSM approach matched a subset of 633 telehealth patients to 1,899 non-telehealth patients with an overall sample of 98,139 visits. We report the results of our three-step IV estimation in Appendix

[18] $\phi(.)$ and $\Phi(.)$ denote the probability density and cumulative distribution functions of a standard normal distribution, respectively. X_2 is the vector of explanatory variables and $\hat{\beta}_2$ is the vector of estimated coefficients from the first stage.
[19] We also conducted an analysis by extending the time window of our DVs to a year and observed consistent results.

Table B6. Our results are qualitatively consistent as patients undergoing telehealth exhibit a reduction in their number of future visits (β_1 =-0.606, p-val < 0.01) and reduction in future costs (β_1 =-2.011, p-val < 0.01). Therefore, we conclude that telehealth use during COVID-19 does not change our main findings.

6.4.6 Exogeneity of IV and Falsification Tests

We performed several tests to ensure the exogeneity of our instruments. We first checked whether *insurance status* and the IV collectively impact our DVs for non-telehealth visits, i.e., if the impact of the IV varies by patient insurance status, then it may suggest confounding (Barron et al. 2021). We did not observe any correlations between these in our graphical plots and empirical estimations. Hence, health insurance status was not observed to change the perceptions of distance between the care location and patient zip code and its impact on telehealth use.

Second, we performed several falsification tests to ascertain that our main independent variable, *Telehealth*, is not prone to randomization concerns and our instrument, *DiffDistance*, is exogenous. First, we checked whether our IV, *DiffDistance*, indirectly predicts future visits and costs for patients who never had a telehealth visit. For these patients, we assigned a *Telehealth* visit at random (i.e., 3% of the visits received *Telehealth* = 1 at random). We report our results in Column 1 of Table B7 in the Appendix, and do not observe any significant results, confirming the validity of our IV.

Third, we implemented three falsification tests to check whether patients' level of health cautious behavior confounds our results and endogenizes our IV, *DiffDistance* (Barron et al. 2021). For this, we implemented a randomization inference test and check whether our IV is correlated with spurious unobserved factors, such as patient's health cautious decisions being driven by access and socio-economic status. We randomly swapped the *Telehealth* variable by (a) patient, (b) zip code, and (c) zip code and insurance status. We provide our results in Table B7, columns 2 through 4. We observe consistently insignificant results after randomization, indicating our IV is not prone to confounding based on patients' health cautious decisions.

Finally, to check whether our telehealth visit variable suffers from uncontrolled confounding issues, we implemented a doubly robust (DR) estimation technique. DR estimation alleviates model misspecification issues not only in the outcome model but also in the treatment assignment model, i.e., telehealth exposure in our case (Sant'Anna and Zhao 2020, Scharfstein et al. 1999). Hence DR concurrently examines the relationships between covariates, exposure, and outcomes, and provides a robust estimate of the impact of exposure on the outcomes (Scharfstein et al. 1999). We implemented a Targeted Maximum Likelihood Estimation (TMLE) to estimate the effect of telehealth exposure on patients' future visits and costs (Gruber and Laan 2009). Our estimation results of the average treatment effect (ATE) are -0.076 with 95% CI of (-0.091, -0,060) and -0.618 with 95% CI of (-0.683, -0.552) for future visits and costs, respectively. Our DR estimation shows qualitatively consistent results, suggesting that model misspecification either in the exposure or the outcome model, does not pose a major concern.

7 DISCUSSION

Technological advancements and the COVID-19 pandemic have accelerated the movement toward telehealth adoption and use in healthcare. Telehealth has the potential to address some of the major challenges facing the U.S. healthcare system with respect to runaway costs and lack of access. By using technology-enabled platforms to deliver health care, patient information, and education, across distant locations, telehealth offers a promising platform to reduce health disparities, especially among disadvantaged populations. However, the challenges in using telehealth for specific diseases and lack of adequate empirical evidence on its impact on resource utilization have raised concerns, requiring a comprehensive examination of its effectiveness on whether and how telehealth can virtualize care (Bestsennyy et al. 2021, Huskamp et al. 2018).

Drawing on the lens of PVT, we study the impact of telehealth on healthcare utilization by leveraging patient visit-level data to examine the use of telehealth in facilitating e-visits between patients and healthcare providers. Specifically, we observe a 13.6% reduction (or 0.15 visits) in the number of outpatient visits, equal to a reduction of $239 in total costs within 30 days after a telehealth visit, suggesting a *substitution effect* of telehealth. Our results reveal that these improvements can be attributed primarily to diseases with care processes that are more amenable to virtualization. For these patients, we observe a 12.2% (or 0.21 visits) reduction in the number of future outpatient visits, equivalent to a cost reduction of $179. Our result supports earlier studies on telehealth use in rural areas where distance (and socio-geographic factors) still matters for telehealth provisioning (Chao et al. 2021, Yeow and Goh 2015). Our results are also consistent with recent research by Delana et al. (2022), who observed an increase in patient visits to tertiary hospitals after the opening of a nearby telemedicine clinic. Furthermore, we observe empirical evidence to support the representation and monitoring capabilities of telehealth in reducing future healthcare utilization.

7.1 Managerial and Policy Implications

Our paper provides actionable managerial and policy implications. Our findings with respect to the differential impact of telehealth based on disease virtualizability depict a striking picture. Telehealth should not be regarded as a one-size-fits-all solution to virtualize healthcare. Telehealth's representation capability may reduce the resistance to virtualization for certain diseases, such as mental health, skin disorders, metabolic, and musculoskeletal disorders. Further, telehealth's monitoring ability to control disease progression and enable follow-up care can lead to a displacement in the timing of healthcare utilization, reducing future visits and costs. However, due to the complexity of care involved, telehealth does not significantly impact the future resource utilization in patients with low virtualizability diseases. However, telehealth may still benefit these patients by providing a platform for initial screening and consultations before treatment. Our results support Overby et al. (2008) and suggest that contextual factors play a role in attenuating or strengthening the virtualization requirements of healthcare processes.

Specifically, our results suggest two important policy prescriptions: (a) mental health, skin disorder, metabolic, and musculoskeletal disease patients should be encouraged to receive healthcare remotely through telehealth, and (b) insurance plans should expand their telehealth coverage to include more providers and close the healthcare access divide in rural locations, which can reduce subsequent hospitalizations and unnecessary costs. The Coronavirus Aid, Relief, and Economic Security (CARES) Act, signed into law in March 2020, loosened restrictions on telehealth services to Medicare patients to encourage greater use of telehealth (Delgado et al. 2020). According to the new CMS 1135 waiver, providers need not be "qualified providers," nor should patients be "established patients" for Medicare to reimburse telehealth consultations. The COVID-

19 pandemic paved the way for greater coverage of telehealth, and these waivers are likely to reduce healthcare disparities, even after the pandemic. However, contextual factors, such as the breadth of diseases covered by telehealth reimbursement, will determine the effectiveness of such efforts. Our research identifies the boundary conditions under which telehealth can be effective in reducing future healthcare utilization.

7.2 Theoretical Implications

Our research contributes to the extant literature on PVT by examining the role of IT constructs - reach, representation, and monitoring - in the context of healthcare. We enrich PVT by showing that the interplay between disease virtualizability and telehealth capabilities, has a significant impact on successful implementation of process virtualization. Furthermore, our study sharpens our understanding of how and when processes can be virtualized and identifies the IT capabilities that are influential in a virtual healthcare setting. Accordingly, we address the call by Overby et al. (2010) to develop a better understanding of process virtualization, the boundary conditions under which care virtualization can work or fail, and the underlying mechanisms that explain process virtualization. By highlighting the differential impact of three types of IT capabilities, we shed greater light on the mechanisms that explain the impact of telehealth on resource utilization, based on the incidence of primary care, ED, and specialist visits, as well as overall costs.

Our research contributes to the health IT literature by showing that telehealth use for specific diseases can lead to lower healthcare utilization and emphasizing the specific dimensions of telehealth capabilities that are instrumental in facilitating improved healthcare outcomes. Furthermore, our research represents one of the first comprehensive empirical studies to quantify the value of telehealth use on population health. Unlike earlier research on the business value of telehealth that relied on hospital- or provider-level use of telehealth, we use a patient visit-level dataset that provides rich insights on the implications of telehealth use on patient utilization across a state-wide heterogeneous population. Our results suggest that telehealth interventions can address some of the extant disparities in healthcare delivery and address a recent call for empirical evidence on the potential of telehealth to reduce healthcare costs (Burch et al. 2017).

7.3 Limitations and Future Directions

Our study is subject to a few limitations. First, we examined the patient population in a single state. To increase its generalizability, future studies may expand its scope to include other states. However, there is no reason to indicate that the state of Maryland is unrepresentative of the US population at large. Second, although we have attempted to address potential confounding factors utilizing PSM and IV methods, we acknowledge that there may still exist other unobserved or confounding factors. Third, we followed the definition of CMS to construct our telehealth variable. Future studies may include other teleservices, such as home-based care through video-monitoring technologies, telemonitoring, and sensor-based mobile health, where telehealth may be more frequent in other contexts. Nevertheless, our study represents a significant step toward developing a comprehensive framework to study the economic and clinical value of telehealth that can be expanded to encompass other types of settings, such as home-based telehealth or remote patient monitoring.

8 CONCLUSIONS

We study the impact of telehealth use on healthcare utilization, across a large, state-wide patient population, and observe that telehealth use is associated with significant reductions in future outpatient visits and healthcare costs. Drawing on the lens of process virtualization theory, we unveil the underlying mechanisms that help us better understand the impact of telehealth on healthcare utilization. Specifically, we find that the representation, reach, and monitoring capabilities of telehealth provide a deeper understanding of process virtualization and its impact on healthcare resource utilization. For instance, the monitoring capability of telehealth can explain its impact on reduction in future PCP visits and costs, while its representation capability allows patients to seek more preventive care which, in turn, is associated with a reduction in specialist visits and overall costs.

Ours is one of the first studies to provide empirical evidence on the mechanisms behind the impact of telehealth use on patient utilization, based on a longitudinal study of a large patient population across several years. Furthermore, we observe that the impact of process virtualization varies significantly based on the virtualizability of different disease types. Specifically, our study highlights the role of IT capabilities in enabling the differential impact of telehealth on future utilization. While the representation capabilities of telehealth are associated with a greater incidence of future primary care visits, they are likely to lead to fewer specialist visits. In a similar vein, telehealth's monitoring capabilities are associated with a lower incidence of future PCP and specialist visits as well as overall costs. Our research also shows that the rural patients are likely to use telehealth as a gateway to utilize more PCP and specialist visits in the future, but their overall costs are likely to be lower. Our study provides a foundation to build on for future research on the impact of other tele-services including remote patient monitoring and other home-based care services.

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Impact of Telehealth and Process Virtualization on Healthcare Utilization

Online Appendix A

Table A1. Comparative Analyses of Related Telehealth Research

Literature & Journal Type	Type	Use/Adopt	Synch.?	Outcome	Disease	Research Method	Data Context	Cross Section or Panel	Study Period
Yan and Tan 2014 (B)	E-health	Use	N	New posts, health state	All	Empirical	Health 2.0 website patients	Panel	16weeks
Goh et al. 2016 (B)				Social support exchanges	Rare disease	Empirical	An online health community (US)	Cross	2005-09
Kelley et al. 2011 (B)		Adopt	N	Antecedents of the eHealth system use, Self-care behavior	Chronic (Diabetes)	Mixed	Building Healthy Lifestyle patients	Panel	18 months
Savoli et al. 2020 (B)	Patient portal	Use	N	Self-management performance	Chronic (Asthma)	Mixed	2 tertiary care hospitals (Canada)	Cross	NA
Bao et al. 2020 (B)				Hospital and ED visits, readmission risk, and LOS	Chronic (CHF)	Empirical	An academic medical center (North Texas)	Panel	2002-14
Erdogan et al. 2018 (B)	Telecystoscopy	Adopt	Y	Schedule of arrival times	Bladder cancer	Modeling	Simulated	NA	NA
Korpeoglu et al. 2014 (B)	Teleradiology	Adopt	Y	Demand	All	Modeling	Visits on the Virtual Radiologic platform	Cross	2011-12
Saghafian et al. 2018 (B)	Teletriage	Adopt	Y	Referral	All	Modeling	Simulated	NA	NA
Cakici and Mills 2020 (B)				Cost, No of ED Visits	Acute	Modeling	Simulated	NA	NA
Singh et al. 2011 (B)	Telemonitoring	Adopt	Y	Post-acute care delivery transformation, clinical and financial outcomes	All	Mixed	THA Group	Cross	2000-09
Liu et al. 2018 (B)		Use	N	Readmission	Bladder cancer (cystectomy)	Modeling	Patients from a regional hospital and 5 state SID files	Cross	2007-12, 2009-10
Paul and McDaniel 2004 (B)	Telehealth (generic)	Adopt	Y	Access, quality, cost	All	Mixed	10 telehealth projects	Cross	NA
Zhou et al. 2021 (B)				Provider earnings, quality of care	All	Empirical	34% of US Physicians	Panel	2012-18
Weiner et al. 2021 (H)	E-visit: Video, phone, message	Use	Y	Ambulatory contacts, telehealth use	All	Empirical	Private insr. patients	Cross	2019-20
Rodriguez et al. 2021 (H)	E-visit: Video, phone	Use	Y	Telehealth use, ED visit, delays in medical care & prescriptions	All	Empirical	Sample of CA residents	Cross	2015-18
Darrat et al. 2021 (H)				Patient demographics, insurance, socioecon. status	Otolaryngology	Empirical	Otolaryngology Dept. Henry Ford HS	Cross	2020
Miscione 2007 (B)	E-visit: Phone, message	Use	Y	Factors impacting Telemedicine adoption	All	Mixed	Upper Amazon Town hospitals	Cross	2003-04
Wang et al. 2020 (B)	E-visit: Message	Use	Y	Online consultations, articles, reviews, gifts, offline visits	All	Empirical	Health 2.0 website physicians	Panel	2010-17
Bavafa et al. 2018 (B)		Adopt	N	No of office visits per month	All	Empirical	A large healthcare system (US)	Panel	2008-13
Hwang et al. 2022 (B)	E-visit: Phone	Use	Y	Geographic healthcare disparity	All	Empirical	A Telehealth company (China)	Panel	2006-15
Bakitas et al. 2020 (H)				Quality of life, mood, paint intensity, pain interference	Palliative	RCT	VA Medical Center (AL)	Panel	2015-19
Huang et al. 2021 (B)	E-visit: Video*	Adopt	Y	Online/Offline Demand, Gift, Rating	All, Chronic	Empirical	Chinese Health Platform	Panel	2017-18
Sun et al. 2020 (B)				ED LOS	All	Empirical	Emergency visits (NY)	Panel	2010-14
Rajan et al. 2019 (B)				Service rate, welfare, revenue	Chronic	Modeling	Simulated	NA	NA
Li et al. 2020 (B)	E-visit: Video	Use	Y	Patient satisfaction	All	Mixed	2 telecamps (India)	Cross	2012
Serrano and Karahanna 2016 (B)				E-consultation Diagnosticity	All	Mixed	Clinicians & A university (US)	Cross	NA
Yeow and Goh 2015 (B)				Wait time uncertainty, admissions, no of consultations	Acute (geriatry)	Mixed	Geriatric Dept.of a hospital	Panel	2010-11
Li et al. 2021 (H)				No of follow up visit, ED visits, urgent care	Acute (respiratory infections)	Empirical	Private insurance claims in a state	Panel	2016-19
Chao et al. 2021 (H)				Telehealth use	Surgical	Empirical	Private insurance claims in a state	Cross	2019-20
Bian et al. 2019 (H)		Adopt	Y	ED visits	Chronic (pediatric)	Empirical	South Carolina child.	Panel	2012-17
This study	**E-visit: Video**	**Use**	**Y**	**No of OP Visits, cost in 30 days**	**All and Chronic**	**Empirical**	**All visits in Maryland**	**Panel**	**2012-18**

Abbreviations: B = Business journal, H = Health, medicine journal. Synch.? = Synchronous? Yes (Y) or No (N). LOS: length of stay. ED: emergency department. E-Health: self-care programs, online support, education, training, online community. E-visit: Video. Mixed: Mixed methods entail a qualitative design followed by a survey, interview, case study, or empirical approach. * Authors do not specify the mode of visit. Video visit is assumed.

Table A2. First Stage Probit Estimation Results of IV Approach

DV:	Telehealth	
Ln(DiffDistance)	0.020***	(0.003)
Ln(PtAge)	0.791***	(0.019)
Ln(PtAge)^2	-0.167***	(0.003)
PtMarried	0.072***	(0.008)
PtOther	0.129***	(0.009)
InsMedicare	0.202***	(0.025)
InsMedicaid	0.027	(0.024)
InsPrivate	0.232***	(0.024)
InsOther	0.220***	(0.029)
Chronic	0.923***	(0.008)
Num_Comorbidities	-0.631***	(0.007)
Ln(PastVisit365D)	0.065***	(0.002)
%PastPCPVisit365D	0.114***	(0.007)
%PastEDVisit365D	-1.067***	(0.038)
Ln(RVU)	0.757***	(0.005)
Patient, Hospital, Quarter Fixed Effect	Included	
Observations	2,869,541	
Pseudo R^2	0.648	

Robust standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table A3. Estimated Impact of Telehealth Using Alternate Instrumental Variables

DV:	IV: Broadband Internet Penetration		IV: Relative Telehealth Use in Peer Zip codes	
Ln(Visit30D)	-0.147***	(0.004)	-0.147***	(0.004)
Ln(Cost30D)	-0.312***	(0.021)	-0.312***	(0.021)
IV: First Stage Coeff.	0.340***		0.001*	
IV: Under ID Test	658.369***		1685.006***	
IV: Weak IV Test	196.448, Bias <10%†		1.2e+04, Bias <10%†	
Controls	Included		Included	
Patient Fixed Effect	Included		Included	
Hospital Fixed Effect	Included		Included	
Quarter Fixed Effect	Included		Included	

* p < 0.10, ** p < 0.05, *** p < 0.01.
† Based on maximal Stock-Yogo critical values. Regression results using 3-step IV estimation. Telehealth coefficients are reported in each cell. Robust standard errors in parentheses.

Table A4. Related Literature on Telehealth Effectiveness across Disease Types

Disease Category	Reference	Consequences of Telehealth Use	Degree of Virtualizability
Endocrine, nutritional, and metabolic diseases	Kelly et al. (2020)	Improved dietary choices, effective weight management, and reduced cost	High
Mental illness	Gellis et al. (2014)	Telepsychiatry patients experience lower depression scores due to reinforced self-efficacy and counseling	High
Diseases of the skin and subcutaneous tissue	Yeroushalmi et al. (2021)	Patients could be provided specialist diagnosis and disease management advice	High
Diseases of the musculoskeletal system	Howard and Kaufman (2018)	A distant specialist can guide the telepresenter during a virtual physical exam	High
Infectious and parasitic diseases	Assimacopoulos et al. (2008)	Infectious disease specialist treatment is equally effective when delivered via telehealth as when delivered via in-person	Medium
Neoplasms	Blackwood and Rybicki (2021)	Limited evidence regarding satisfactory outcomes of telehealth-delivered physical activity programs in cancer survivors	Low
Diseases of the blood and blood-forming organs	Shaner et al. (2021)	Telehealth did not show any difference in laboratory response to hydroxyurea for patients with sickle cell anemia.	Medium
Diseases of the nervous system and sense organs	Chen et al. (2020)	Telehealth intervention lowered motor impairment of Parkinson's Disease patients but had no impact on mental status or quality of life.	Medium
Diseases of the circulatory system	Grustam et al. (2014)	Telehealth's cost-effectiveness in chronic heart failure remains unknown in peer-reviewed literature.	Low
Diseases of the respiratory system	Bakhit et al. (2021)	Telehealth can lead to increases in healthcare resource utilization such as antibiotic prescription for acute infections.	Low
Diseases of the digestive system	Wegermann et al. (2022)	Telehealth use for liver disease treatment of vulnerable populations increased the risk of telephone visits compared to video visits	Low
Diseases of the genitourinary system	Lunney et al. (2018)	Telehealth interventions showed mixed or insignificant results on processes of care and laboratory surrogate markers of end-stage renal disease care.	Medium
Complications of pregnancy, childbirth	Öztürk et al. (2022)	Telehealth and routine care yielded similar maternal/neonatal health and cost outcomes.	Medium
Congenital anomalies	Cooper et al. (2020)	Telehealth home monitoring program intervention for congenital heart disease was not associated with an improvement in parent or infant outcomes.	Medium
Certain conditions originating in the perinatal	Duryea et al. (2021)	After the implementation of audio-only prenatal virtual visits, women who delivered did not show more adverse pregnancy outcomes than women who delivered before the implementation	Medium
Injury and poisoning	Cummins et al. (2013)	Inefficiencies and vulnerabilities occur in telephone-based poison control centers– emergency department communication.	Low

This table only contains illustrative examples of current literature on telehealth.

Table A5. Expert Rating of Disease Categories on Telehealth's Ability to Virtualize Care Processes

	Telehealth's Ability to Virtualize Care			
Disease Category:	**Reach**	**Monitoring**	**Represent.**	**Overall**
Endocrine, nutritional, and metabolic diseases	H	H	H	**H**
Mental illness	H	H	H	**H**
Diseases of the skin and subcutaneous tissue	H	H	H	**H**
Diseases of the musculoskeletal system	H	H	H	**H**
Infectious and parasitic diseases	L	L	L	**L**
Neoplasms	L	H	L	**L**
Diseases of the blood and blood-forming organs	L	L	L	**L**
Diseases of the nervous system and sense organs	L	L	L	**L**
Diseases of the circulatory system	L	H	L	**L**
Diseases of the respiratory system	H	L	L	**L**
Diseases of the digestive system	L	L	L	**L**
Diseases of the genitourinary system	L	L	L	**L**
Complications of pregnancy, childbirth	L	L	L	**L**
Congenital anomalies	L	L	L	**L**
Certain conditions originating in the perinatal	L	L	L	**L**
Injury and poisoning	L	L	L	**L**

Survey data based on practitioner feedback collected primarily from a leading academic medical center in the U.S.
H refers to high ability when the average response score for a specific disease and telehealth ability combination is more than the overall average response plus 0.5 standard deviation.
L refers to low ability and is given if the average score is less than the overall average response plus 0.5 standard deviation for a specific disease and telehealth ability combination.
Overall takes H (L) if two out of three abilities are rated H (L) for a specific disease.

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Online Appendix B

Figure B1. High vs Low Representation Encounters: 30 Day Cost Analysis by Visit Type and Year

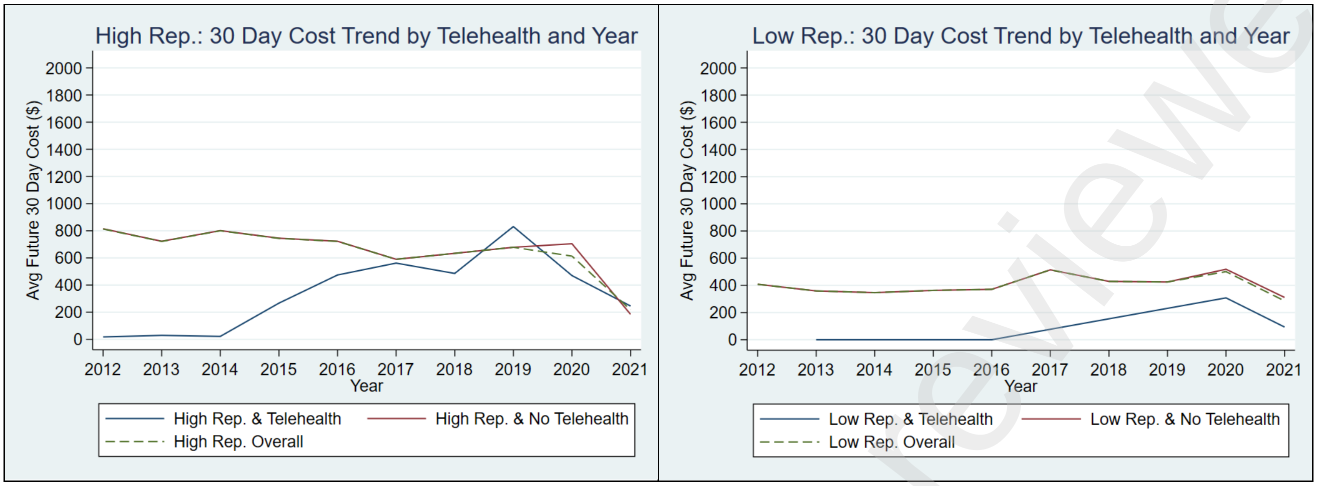

Table B1. Summary of Matching Criteria Used in CEM Approach

Name	# of Categories	Categories
Patient Age	6	0-7; 8-18; 19-35; 36-50; 51-65; 66+
Patient Marital Status	3	Married; Other; Single
Patient Race	3	Black; Other; White
Patient Sex	3	Female; Male; Other
Insurance	5	Medicare; Medicaid; Other; Private; Selfpay
Number of Comorbidities	3	0; 1; 2+
Past Visits within 365 days	6	0; 1; 1-6; 7-17; 18-32; 32+

Table B2. Variable Imbalance Statistics Before and After CEM

	Before CEM L1 = 0.468		**After CEM L1 = 0.330**	
Matching Variables:	**Mean Difference (Treatment – Control)**	**L1**	**Mean Difference (Treatment – Control)**	**L1**
PtAge	7.986	0.187	-0.006	0.052
PtMarried	0.082	0.082	0.000	0.000
PtMariStatOther	0.021	0.021	0.000	0.000
PtSingle	-0.103	0.103	0.000	0.000
PtRaceBlack	0.091	0.091	0.000	0.000
PtRaceOther	-0.050	0.050	0.000	0.000
PtRaceWhite	-0.041	0.041	0.000	0.000
PtFemale	0.009	0.009	0.000	0.000
PtSexUnknown	0.000	0.000	0.000	0.000
PtMale	-0.009	0.009	0.000	0.000
InsMedicare	0.072	0.072	-0.014	0.014
InsMedicaid	-0.012	0.012	0.109	0.109
InsPrivate	-0.059	0.059	-0.084	0.084
InsOther	-0.003	0.003	-0.009	0.009
InsSelfpay	0.003	0.003	-0.002	0.002
Num_Comorbidities	0.263	0.200	0.001	0.000
PastVisit365D	-2.658	0.247	1.239	0.039

Table B3. Estimation Results for Healthcare Utilization using Coarsened Exact Matching

DV:	Ln(Visit30D)		Ln(Cost30D)	
Telehealth	-0.267***	(0.008)	-0.162***	(0.033)
Ln(PtAge)	0.034***	(0.004)	0.386***	(0.016)
Ln(PtAge)^2	-0.010***	(0.001)	-0.076***	(0.003)
PtMarried	0.003*	(0.002)	0.089***	(0.008)
PtOther	0.017***	(0.002)	-0.024***	(0.009)
PtRaceBlack	-0.029***	(0.001)	-0.112***	(0.006)
PtRaceOther	0.003	(0.002)	-0.007	(0.008)
PtFemale	-0.010***	(0.001)	0.044***	(0.005)
InsMedicare	-0.040***	(0.006)	0.288***	(0.025)
InsMedicaid	0.136***	(0.006)	0.466***	(0.024)
InsPrivate	0.008	(0.006)	0.454***	(0.024)
InsOther	0.098***	(0.007)	0.639***	(0.029)
Chronic	-0.016***	(0.002)	0.633***	(0.007)
Num_Comorbidities	0.084***	(0.002)	0.216***	(0.007)
Ln(PastVisit365D)	0.256***	(0.001)	1.081***	(0.003)
%PastPCPVisit365D	-0.181***	(0.002)	-0.458***	(0.007)
%PastEDVisit365D	-0.097***	(0.009)	-0.392***	(0.039)
Ln(RVU)	-0.059***	(0.003)	-0.033***	(0.011)
Constant	0.297***	(0.009)	0.326***	(0.040)
Patient Time-invariant Effects†	Included		Included	
Patient Fixed Effects	Not Included		Not Included	
Hospital Fixed Effect	Included		Included	
Quarter Fixed Effect	Included		Included	
Observations	1,204,230		1,204,230	
R^2	0.445		0.383	

Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.
†As the observations are weighted by their CEM propensity scores, patient fixed effects became collinear with the binary treatment variable, *Telehealth*. Hence, we included time-invariant patient effects, race and gender

Table B4. Estimation of Healthcare Utilization using Heckman Selection

DV:	Ln(Visit90D)		Ln(Cost90D)	
Telehealth	-0.121***	(0.010)	-0.229***	(0.031)
Ln(PtAge)	0.023**	(0.010)	0.086**	(0.035)
$Ln(PtAge)^2$	-0.010***	(0.004)	-0.029**	(0.012)
PtMarried	-0.008	(0.006)	-0.011	(0.019)
PtOther	0.007	(0.006)	-0.003	(0.017)
InsMedicare	-0.107***	(0.011)	0.061**	(0.027)
InsMedicaid	0.047***	(0.008)	0.237***	(0.021)
InsPrivate	-0.015*	(0.008)	0.236***	(0.023)
InsOther	0.105***	(0.013)	0.416***	(0.034)
Chronic	0.081***	(0.002)	0.774***	(0.008)
Num_Comorbidities	-0.015***	(0.001)	-0.106***	(0.006)
Ln(PastVisit365D)	0.167***	(0.002)	0.930***	(0.005)
%PastPCPVisit365D	-0.143***	(0.003)	-0.424***	(0.008)
%PastEDVisit365D	-0.089***	(0.004)	-0.258***	(0.018)
Ln(RVU)	-0.022***	(0.002)	0.009*	(0.005)
MillsRatio	0.066***	(0.006)	0.162***	(0.019)
Constant	0.300***	(0.029)	1.357***	(0.092)
Patient, Hospital, Quarter Fixed Effect	Included		Included	
Observations	2,874,463		2,874,463	
R^2	0.159		0.149	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5. Estimation of Healthcare Utilization within a 90-day window

DV:	Ln(Visit90D)		Ln(Cost90D)	
Telehealth	-0.233***	(0.005)	-0.625***	(0.022)
Ln(PtAge)	0.042***	(0.004)	0.034	(0.023)
$Ln(PtAge)^2$	-0.013***	(0.001)	-0.018***	(0.007)
PtMarried	-0.012***	(0.002)	-0.011	(0.011)
PtOther	0.009***	(0.002)	-0.016	(0.010)
InsMedicare	-0.097***	(0.003)	0.287***	(0.015)
InsMedicaid	0.069***	(0.003)	0.345***	(0.013)
InsPrivate	0.008**	(0.003)	0.366***	(0.014)
InsOther	0.100***	(0.004)	0.431***	(0.017)
Chronic	0.208***	(0.001)	1.372***	(0.004)
Num_Comorbidities	-0.043***	(0.001)	-0.179***	(0.004)
Ln(PastVisit365D)	0.288***	(0.001)	1.179***	(0.002)
%PastPCPVisit365D	-0.133***	(0.001)	-0.069***	(0.005)
%PastEDVisit365D	-0.144***	(0.002)	-0.245***	(0.012)
Ln(RVU)	0.007***	(0.001)	0.137***	(0.003)
Patient, Hospital, Quarter Fixed Effect	Included		Included	
Observations	2,869,541		2,869,541	
R^2	0.233		0.225	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6. Impact of Telehealth on Healthcare Utilization prior to 2020 (i.e., pre-COVID-19)

DV:	Ln(Visit30D)		Ln(Cost30D)	
Telehealth	-0.606***	(0.018)	-2.011***	(0.086)
Ln(PtAge)	0.011	(0.013)	0.884***	(0.057)
$Ln(PtAge)^2$	0.001	(0.002)	-0.187***	(0.010)
PtMarried	0.003	(0.008)	0.085***	(0.029)
PtOther	0.028***	(0.007)	0.043*	(0.025)
InsMedicare	-0.217***	(0.020)	0.272***	(0.075)
InsMedicaid	0.067***	(0.020)	0.194***	(0.074)
InsPrivate	-0.131***	(0.021)	0.315***	(0.076)
InsOther	-0.093***	(0.023)	0.524***	(0.086)
Chronic	0.090***	(0.005)	1.457***	(0.024)
Num_Comorbidities	0.001	(0.004)	-0.119***	(0.021)
Ln(PastVisit365D)	0.351***	(0.002)	1.064***	(0.007)
%PastPCPVisit365D	-0.354***	(0.006)	-0.906***	(0.032)
%PastEDVisit365D	-0.145***	(0.013)	-0.197***	(0.073)
Ln(RVU)	-0.123***	(0.005)	-0.047***	(0.017)
Patient Fixed Effect	Included		Included	
Hospital Fixed Effect	Included		Included	
Quarter Fixed Effect	Included		Included	
Observations	98,137		98,137	
R^2	0.360		0.318	

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table B7. Falsification Test Results

	(1) Only non-telehealth patients		(2) Randomize by patient		(3) Randomize by zip code		(4) Randomize by zip code and insurance status	
DV:	Ln(Visit30D)		Ln(Visit30D)		Ln(Visit30D)		Ln(Visit30D)	
Telehealth	-74.284	(169.821)	64.230	(65.678)	23.225	(17.213)	-690.212	(15890.365)
Patient, Hospital, Quarter Fixed Effect	Included		Included		Included		Included	
Observations	1,575,365		2,869,541		2,869,541		2,869,541	
DV:	Ln(Cost30D)		Ln(Cost30D)		Ln(Cost30D)		Ln(Cost30D)	
Telehealth	-239.531	(548.139)	-53.817	(55.925)	116.360	(86.393)	-3066.110	(70589.522)
Patient, Hospital, Quarter Fixed Effect	Included		Included		Included		Included	
Observations	1,575,365		2,869,541		2,869,541		2,869,541	

Robust standard errors are in parentheses
* p<0.10, ** p<0.05, *** p<0.01