Health Outcomes, Information Costs, and the Rise of Telehealth during the COVID-19 Pandemic

Austin Knies

Department of Economics, Indiana University, Bloomington, IN, USA*

April 2024

Abstract

How has the increase in synchronous telemedicine services throughout the COVID-19 pandemic impacted patient health outcomes? Using 2018-2022q1 claims data from Optum's de-identified Clinformatics® Data Mart Database, I examine differences in telehealth and face-to-face care for office and outpatient evaluation and management (E/M) service claims, where telehealth coding has been the most frequent. Telehealth usage is associated with higher likelihood of patient mortality and ER visit within 6 months of E/M service claim, where I find an average effect of 5 additional deaths and 13 additional ER visits per 1,000 patients in the post-March 2020 period. To explain observed differences in health outcomes across visit modalities, I model the physician-patient interaction as a costly information acquisition problem, where rationally inattentive physicians learn about the patient's health status through costly signals. Estimated increases in information costs with telehealth usage range between 5 to 29 percent on average after March 2020. These findings quantify the consequences of using telehealth as a substitute for in-person care.

Keywords: telehealth, telemedicine, rational inattention, COVID-19, health care. *JEL codes: I10, D83*

*Email address: ausknies@iu.edu.

I am grateful to Emerson Melo, Seth Freedman, Kosali Simon, Coady Wing, Volodymyr Lugovskyy, Stefan Weiergraeber, Angela Campbell, Jia Xiang, Jonathan Leslie, Jack Berger, members of IU's O'Neill School Health Policy Workshop, and seminar participants at the 2023 EEA, MEA, and ASHEcon meetings for their valuable feedback.

1 Introduction

Telehealth and telemedicine, or the use of telecommunications technologies in the provision of health care services, surged in popularity at the onset of the COVID-19 pandemic, both in the United States (Brotman and Kotloff (2021)) and throughout the world (Nittari et al. (2022)). Despite little and infrequent uptake prior to the COVID-19 lockdowns, telehealth was seen as essential in the early stages of the pandemic as a means to increase access to care and reduce the risk of spreading COVID-19 through face-to-face contact (Smith et al. (2020)). Going forward, however, how and to what extent telemedicine should be involved in our health care systems is an open question for health care providers, payers, patients, and policymakers.

While the expansion of telehealth has potential to address deficiencies in health care provision, less is known about the impact of telehealth usage on health outcomes. In this paper, I examine the differences in telehealth and face-to-face care before and throughout the COVID-19 pandemic across the United States. With this recent widespread rise in telehealth services, I investigate the following question: how does telehealth usage impact patient health outcomes in its most frequent form, that is, when used in place of in-person care? As I address this question, I also consider what mechanisms lead to observed differences in outcomes across visit modalities, namely differences in informational limitations in patient and provider interactions.

Using claims data from Optum's de-identified Clinformatics® Data Mart Database, I first trace the evolution of telehealth and face-to-face visits for commercially insured and Medicare Advantage patients across the United States from 2018 to 2022. Where the existing literature mostly describes the rise in telemedicine within samples of smaller scale and scope, I provide a characterization across patients and providers within a nationwide private health insurance claims database. With this evolution, I focus on office and outpatient evaluation and management (E/M) service visits, where telehealth usage is most frequent across all observed health care claims. I find that telehealth usage peaks in April 2020 and declines but never returns to pre-pandemic levels. In addition, I find that telehealth usage varies more by provider after March 2020.

Next, I connect the evolution in telehealth usage before and during the COVID-19 pandemic to patient health outcomes. Formally, I use a reduced-form empirical approach to investigate the impact of using synchronous audio/video telehealth appointments in place of face-to-face visits on severe health outcomes. By analyzing effects on mortality and ER visits at the encounter, patient, and provider levels, I show that telehealth usage is associated with higher likelihood of a severe health outcome within 6 months of an office/outpatient E/M visit. In the typical month following March 2020, I find the average marginal effect of telehealth usage on patient health outcomes is approximately 5 additional deaths and 13 additional ER visits per 1,000 patients. These findings are novel, in that there is a lack of literature connecting substitutionary telehealth usage and health outcomes prior to March 2020 or beyond. Yet, these findings reinforce the existing literature linking pre-pandemic telehealth usage and health outcomes, which suggest that the strengths of telehealth may reside in expanding access to care for low-risk patients and as a complement to in-person care.

Accompanying these primary empirical findings are a series of additional specifications, robustness checks, and sensitivity analyses where I account for factors that may contribute to selection bias and confounding. These alternative approaches serve as further support for the overall conclusions I observe in the main empirical results. In one alternative approach, I use an inverse propensity score weighting to improve balance in observed patient, provider, and visit characteristics. In another alternative approach, I use an instrumental variable to address potential endogeneity in telehealth use, where I construct a leave-one-out measure of a medical provider's tendency toward telehealth use. Further checks and sensitivity analyses on additional factors and characteristics of the data combine to show that the connection between telehealth use and increased likelihood of subsequent adverse health outcomes is robust.

Finally, I introduce a model of costly information acquisition to capture the physician-patient interaction of a visit, where rationally inattentive physicians seek to assess accurately a patient's health status, subject to a costly information signal. This builds on the literature of information frictions in health care by extending the use of rational inattention models beyond the context of health insurance. In this setup, differences across visit modalities are represented as differences in the marginal cost of information. With this, I provide a mechanism to explain the contrast in patient health outcomes observed between telehealth and face-to-face care. Additionally, I pair the model with the empirical results from the reduced-form analysis to calculate the change in information costs across visit modalities. Using the empirical results on provider 6-month patient mortality rates, I find telehealth usage induces between a 25 to a 29 percent increase on average in physician information costs; for ER visit rates, I find between a 5 to 8 percent increase.

As we move beyond the COVID-19 pandemic, there is increasing complexity in deciding what mixture of goods and services should make up the bundle of health care that patients receive. This paper identifies the trade-offs of increased telehealth usage in terms of information frictions and health outcomes and, in doing so, clarifies the bounds of telehealth usage in the provision of care.

1.1 Literature Review

With this work, I contribute to three sets of existing literature. The first set of literature explores the roll-out of telehealth usage centered around the context of the COVID-19 pandemic. Within the United States, Brotman and Kotloff (2021) summarize the changes in legality and reimbursement of telemedicine as the COVID-19 pandemic arose for commercial insurance, Medicaid, and Medicare populations. Whaley et al. (2020) denote a quick surge in telemedicine for commercially insureds, and the U.S. Department of Health and Human Services noted a 63-fold increase in telehealth usage in the Medicare population alone (Samson et al. (2021)). In international contexts, Busso et al. (2022) show a 230 percent increase in telemedicine calls in Argentina, and Nittari et al. (2022) examine how telehealth usage has changed in over 14 different countries.

There is a growing subset of this set of literature looking at the heterogeneous uptake in telehealth usage across patient types both in the United States (Jaffe et al. (2020), Cantor et al.

(2021), Patel et al. (2021a), Patel et al. (2021b), Rodriguez et al. (2021), Larson et al. (2022)) and internationally (Bhatia et al. (2021), Reges et al. (2022)). There is a small subset of this work, such as Whaley et al. (2022), Choi et al. (2022), and Bose et al. (2022), finding that patients belonging to disadvantaged socioeconomic and demographic groups are more likely to use telehealth, usually under a set of strict circumstances. In general cases, the existing literature finds evidence that obstacles like lower income, age, rurality, or limited broadband access make it less likely for patients to use telehealth. There is also work examining the decline in face-to-face visits alongside the rise in telehealth usage during the COVID-19 pandemic, such as Ziedan et al. (2020) and Uscher-Pines et al. (2021).

I contribute to the literature on telehealth usage as a result of the COVID-19 pandemic by documenting telehealth usage for office/outpatient E/M service claims prior to and throughout the COVID-19 pandemic. These claims are the most significant source of telehealth coding in the data set I employ. I describe this evolution alongside face-to-face visits for the same type of services for both commercially insured and Medicare Advantage plan members who receive care contained in a comprehensive commercial claims database with coverage in all 50 U.S. states. I also explore how providers have changed in offering telehealth services as a share of their overall monthly health care services.

Additionally, while most aforementioned studies remain descriptive and documentary, I link this evolution in telehealth usage to differences in patient health outcomes. There is an existing set of literature that connects the two, but most of these studies examine telehealth usage prior to the COVID-19 pandemic and in settings where telehealth often serves as a complement to in-person care (Uscher-Pines and Mehrotra (2014), Steventon et al. (2016), Armaignac et al. (2018), Reed et al. (2021)). Ekeland et al. (2010) and Snoswell et al. (2021) perform systematic literature reviews of telemedicine analyses conducted before 2020 across several medical disciplines, finding either improvements in care delivery through telehealth usage or no difference from observed in-person care. However, differences in innovation, regulation, and practice from before the COVID-19 pandemic to the present make it difficult to draw inferences for the recent rise in telehealth usage. In contrast to this existing literature, I study telehealth usage before and during the COVID-19 pandemic in claims where telehealth serves as a substitute to face-to-face care.

More recent work has begun to link the rise in telehealth use as a result of the COVID-19 pandemic to impacts on quality and delivery of care. A recent paper in Zeltzer et al. (2023) studies the impact of telemedicine adoption during the COVID-19 pandemic in Israel, finding no evidence of adverse health outcomes as a result of increased telemedicine. However, this study focuses on the context of primary care in the early lockdown phase of the COVID-19 pandemic in Israel. In contrast, I examine problem-oriented outpatient care across the United States, including care delivered by primary care physicians and other medical provider specialties and professionals, where I study telemedicine and face-to-face care two years before and after March 2020. In doing so, I offer novel results showing that telehealth usage is associated with higher likelihood of patient mortality and ER visit within 6 months of a claim, even when controlling for health factors such as a COVID-19 diagnosis and Charlson Comorbidity Index (CCI).

I also contribute to the literature of information frictions in economic models of decision-making, namely the literature on rational inattention originating with Sims (2003). The foundations of this literature lie within monetary economics and information theory (Cover and Thomas (2006), Maćkowiak and Wiederholt (2009)), but it has since spread into more applied settings (Matějka and McKay (2015), Caplin and Dean (2015), Maćkowiak et al. (2021)). In the context of health economics, there is existing literature studying the role of information frictions in decision-making (Abaluck and Gruber (2011), Kling et al. (2012), Handel and Kolstad (2015), Handel et al. (2019)), including rational inattention (Brown and Jeon (2021), Brown and Jeon (2023)). However, these studies are entirely limited to the context of insurance choice. In this paper, by modeling the physician-patient interaction during each visit as a costly information acquisition problem, I apply the rational inattention framework to a new context, providing a mechanism to explain differences in health outcomes across visit modalities and a method of quantifying these differences in terms of information costs.

The remainder of this paper proceeds as follows. Section 2 introduces the model capturing the physician-patient interaction. Section 3 describes the data and and characterizes the evolution of telehealth usage and provider behavior as motivation. Section 4 details the primary reduced-form estimation approach as well as a set of alternative approaches and the model-based estimation of information costs. Section 5 discusses the results of these estimation strategies, and Section 6 concludes.

2 Theoretical Framework

In this section, I apply a rational inattention model to depict the physician-patient interaction during a visit. This model will provide a means to explain the differences in severe health outcomes across visit modalities that will be observed in later sections, as well as to quantify the difference in information costs between one visit modality and another. Formally, I begin with a quadratic-Gaussian rational inattention model that incorporates a loss function as the objective function as detailed in Maćkowiak et al. (2021) and used in price-setting contexts of previous literature (Sims (2003), Maćkowiak and Wiederholt (2009), Wiederholt (2010)).

A rationally inattentive physician seeks to maximize care provided by approximating the patient's true health status as accurately as possible, subject to the information cost of a signal on health status:

$$\max_{s} \quad \mathbb{E}_x[U(y(s), x)] - \lambda I(y(s); x) \tag{1}$$

$$\text{where} \quad U(y, x) = -r(ax - y(s))^2 \tag{2}$$

$$\text{and} \quad x \sim \mathbb{N}(0, \sigma_x^2) \tag{3}$$

Here, x is the true health status of the patient, which is not perfectly known, and y is the physician's approximation of the patient's health status, which depends on costly signal s observed through information channel $I(y(s); x)$. In this setup, $I(y(s); x)$ represents the standard Shannon mutual information assumption following Cover and Thomas (2006), such that information learned by the physician is represented as the reduction in entropy of x from observing s and approximating $y(s)$. In the visit setting, $I(y(s);x)$ represents the visit modality used to establish the interaction between the patient and physician. In this paper, I will consider two mutually exclusive visit modalities: face-to-face care or care through telehealth or telemedicine services.

The objective function in Equation 2 is a loss function which captures the physician's goal of being as accurate as possible in determining the patient's health status, given the marginal cost $\lambda \geq 0$ of paying attention to signal s through $I(y(s);x)$. Here, the parameter $a > 0$ scales the random health status of x, and $r > 0$ governs the severity of misdiagnosis. Intuitively, these parameters permit an arbitrary range of scenarios in delivering care, allowing from low to high variance across both underlying health status and diagnostic outcomes.

Since I let the prior distribution of x be Gaussian as shown in Equation 3, then Gaussian signals chosen by the physician are not only optimal but unique, and the maximization problem can be written in terms of the prior and posterior variance, yielding a tractable solution.[1] With the entropy of a normally distributed random variable accounted for, the entire problem is equivalent to choosing attention strategy $\xi \equiv \left(1 - \sigma^2_{x|s}/\sigma^2_x\right) \in [0,1]$, such that the optimal attention strategy is characterized as

$$\xi^* = \max\left(0, 1 - \frac{\lambda}{2ra^2\sigma^2_x}\right). \tag{4}$$

The optimal attention strategy in Equation 4 provides a set of key implications that will be important in the following sections. First, note that for non-zero equilibrium attention values, a higher information cost λ leads to lower attention strategy ξ^*, or, more formally, $\frac{\partial \xi^*}{\partial \lambda} < 0$. Second, for non-zero equilibrium attention values to occur, the information cost λ is bounded between 0 (where $\xi^* = 1$) and the multiplicative term of underlying model parameters $2ra^2\sigma^2_x$. For $\lambda \geq 2ra^2\sigma^2_x$, the optimal attention strategy is $\xi^* = 0$. These implications will be pivotal to the identification strategy in the following sections.

2.1 Welfare

Given the ability to obtain a closed-form analytical solution in the preceding section, I now show how welfare changes when there are changes in visit modalities. In this context, I will refer to each visit modality as an information regime. To begin, I will use an example of switching between a high-cost regime and a low-cost regime that will be relevant for the empirical strategy and estimation of information costs to follow. Second, I will introduce the general case, which considers any degree of switching, and derive the necessary conditions for determining whether welfare is gained or lost.

In the context of this model, welfare is specific to the rationally inattentive physician. However, because the utility of the physician is modeled as a function of diagnostic concordance,

[1] Maćkowiak et al. (2021) discuss optimal Gaussian signals and their popularity in the literature, and Matějka and McKay (2015) discuss uniqueness.

the physician's indirect utility under an equilibrium attention strategy is a measure that also reflects the representative patient's well-being. Therefore, while I consider welfare of the individual physician, there is a direct correspondence to the welfare of patients who are seen by the physician. Similarly, a natural connection can be made to the indirect effects on social welfare, such as reduced congestion in emergency care when patients are more accurately assessed.

Let us first suppose that we want to understand the differences in welfare between two distinct information regimes. First, I assume that the non-modality characteristics of the physician-patient interaction are identical across regimes. Ceteris paribus, a change in visit modality results in a change in the marginal cost of information.[2] With this assumption, the low-cost regime L has an information cost λ_L, which differs from the marginal cost of information for high-cost regime H (λ_H). Now, given different information costs which generate different optimal attention strategies, I can derive the rationally inattentive physician's indirect utility function for each regime's attention strategy:

$$V = \max_{\xi \in [0,1]} \left[-ra^2(1-\xi)\sigma_x^2 - \frac{\lambda}{2}\log_2\left(\frac{1}{1-\xi}\right)\right], \tag{5}$$

implying that, under regime M,

$$V_M^* = -ra^2(1-\xi_M^*)\sigma_x^2 - \frac{\lambda_M}{2}\log_2\left(\frac{1}{1-\xi_M^*}\right) \qquad \forall M \in \{L, H\}. \tag{6}$$

To look at welfare differences in the two-regime case, we can look at the difference in indirect utility functions, $V_H^* - V_L^*$. Here, let us make explicit that that we assume the marginal cost of information is higher in the high-cost regime; that is, we assume $\lambda_H > \lambda_L$. Note that the optimal attention strategy is higher under $F2F$ than TH: $\xi_H^* < \xi_L^*$. Thus, we have

$$V_H^* - V_L^* = \underbrace{ra^2(\xi_H^* - \xi_L^*)\sigma_x^2}_{\text{difference in utility}} \underbrace{+\frac{\lambda_H}{2}\log_2(1-\xi_H^*) - \frac{\lambda_L}{2}\log_2(1-\xi_L^*)}_{\text{difference in information channel}}. \tag{7}$$

Equation 7 reveals that differences in information costs affect welfare through two distinct mechanisms. The first term in this equation reflects changes in the loss function, or differences in utility, as a result of differences in optimal attention strategies. The second set of terms reflects the changes in the information channel as a result of higher information costs. Together, these two mechanisms combine to cause a change in welfare from switching information regimes.

However, these two channels do not necessarily impact welfare in the same direction, and we must further derive under what condition we expect increases or decreases in welfare. Moving to the general case where we consider a marginal change in information regimes, we can use Equation 6 to find the condition such that increased information costs are welfare-decreasing under nonzero equilibrium attention values. First, note that information costs under any regime

[2] One might reasonably think that signals are noisier across regimes; however, in this model, $\sigma_{x|s}^2$ is endogenous to the physician. Thus, differences in information costs are the margin by which changes in the information channel will be reflected.

M can be written as

$$\lambda_M = \gamma_M \times 2ra^2\sigma_x^2, \tag{8}$$

where $\gamma_M \in [0, 1]$ represents the share of underlying model parameters that contribute to the marginal cost of information. This comes from the fact that $\lambda_M \in [0, 2ra^2\sigma_x^2]$ under nonzero equilibrium attention values. Because the log function is undefined at $\gamma_M = \lambda_M = 0$, and since this trivial case represents the perfect information case, I will go forward assuming $\lambda_M \in (0, 2ra^2\sigma_x^2]$ and $\gamma_M \in (0, 1]$.

Then for $\xi_M^* > 0$ we have

$$\begin{aligned} V_M^* &= -ra^2\left(\frac{\lambda_M}{2ra^2\sigma_x^2}\right)\sigma_x^2 - \frac{\lambda_M}{2}\log_2\left(\frac{2ra^2\sigma_x^2}{\lambda_M}\right) \\ &= \frac{2ra^2\sigma_x^2}{2}\left(\gamma_M \log_2(\gamma_M) - \gamma_M\right) \quad \text{where } \gamma_M \in (0, 1]. \end{aligned} \tag{9}$$

From Equation 9, we have

$$\frac{\partial V_M^*}{\partial \gamma_M} = \frac{2ra^2\sigma_x^2}{2\ln(2)}\left(1 + \ln(\gamma_M) - \ln(2)\right) \tag{10}$$

such that $\dfrac{\partial V_M^*}{\partial \gamma_M} < 0$ iff

$$\gamma_M < \exp\left(\ln(2) - 1\right) \approx 0.73575888234. \tag{11}$$

Intuitively, an increase in the marginal cost of information is welfare-decreasing as long as the baseline information cost is a low to moderate share of underlying model parameters. Therefore, welfare gains from increasing information costs will only occur under relatively high-cost regimes. In these cases, optimal attention strategy ξ_M^* is very low for the physician. Switching to a regime with even higher information costs would be be welfare-improving: despite the decrease in utility from less accurate assessments of health status, the physician is on net better off through saving on information costs after paying even less attention in equilibrium. However, when the condition in Equation 11 is met, the opposite is true; under relatively low- to moderate-cost regimes, higher information costs are welfare-decreasing since the loss in utility is larger than information savings through lower equilibrium attention.

I will base the empirical strategy and estimation of information costs to come on the assumption that the condition in Equation 11 is, in fact, satisfied, i.e., that information costs are sufficiently low and optimal attention strategies are sufficiently high. This assumption will be justified through appealing to the nature of the data and visit modalities explored in the following sections.

3 Data and Motivation

I now move to describing the data used for the empirical analysis and estimation procedures. As a motivation for the sections to follow, I then employ the data to characterize the evolution of telehealth and face-to-face usage before and throughout the COVID-19 pandemic. This will provide a context for testing the impacts of telehealth usage on severe health outcomes in patients, as well as recovering physician information costs from the rational inattention model.

3.1 Data

To study the rise in telehealth usage, I use medical and diagnosis claims data from Optum's de-identified Clinformatics® Data Mart Database. These data are administrative claims data consisting of claims across all 50 U.S. states, covering approximately 67 million unique commercial and Medicare Advantage plan members.[3] Claims data are de-identified at both patient and provider levels, but anonymized identifiers make it possible to track unique patients and providers across time. I pair claims data with enrollment data to obtain patient characteristics, such as age, insurance type, gender, date of death, and race, as well as provider data, such as the state of operation.[4]

For medical claims data, I obtain observations between 2018q1 to 2022q1. By looking two years pre- and post-2020q1, I am able to trace the evolution of telehealth usage prior to and throughout the COVID-19 pandemic. To ensure observations are followed by a full 6-month window to check for associated severe health outcomes, I limit the empirical analysis to claims data through 2021q3. A key part of the empirical analysis will also be dealing with underlying health status through diagnosis data. To do so, I will use COVID-19 diagnoses at the time of claim and Charlson Comorbidity Index (CCI) measures for each patient with a four-quarter look-back period, with the earliest time period being the first quarter of 2017.

With the focus of examining telehealth usage substituted for in-person care, I limit the medical claims data to office and outpatient evaluation and management (E/M) service claims. These claims are identified through Current Procedural Terminology (CPT®) codes 99201-99205 for new patients and 99211-99215 for established patients. Office/outpatient E/M service claims are inherently problem-oriented: a physician or medical professional considers the patient's medical history, conducts an examination, and provides a diagnosis along with any further recommendations. These codes exclude preventive medicine or wellness check-up visits; separate coding procedures exist for these excluded types of health care services. Similarly, these codes exclude other commonly sought forms of evaluation, such as psychotherapy.

When used in an office/outpatient E/M service claim, telemedicine delivery is provided in a synchronous audio/video format. Other forms of telehealth usage such as audio-only E/M

[3]Lee et al. (2021) discusses the similarities in patient characteristics of this data and the population of commercially insured individuals in the United States.

[4]Under this view of the data, accessing patient data on date of death and race prohibits the simultaneous use of geographical information, such as patient ZIP code, or socioeconomic status variables, such as income or education.

service calls or telehealth usage complementing in-person care require a different set of CPT® codes and therefore are excluded from the claims data I study. To identify whether telehealth has been used for an office/outpatient E/M service claim, I check for the presence of CPT® modifier −95 or for place-of-service code 02 or 10. While the guidance on coding claims for telehealth usage differed by insurance type throughout the pandemic, this check ensures I am capturing telehealth usage in claims for both commercial and Medicare Advantage plan members. Additionally, because telehealth and face-to-face office/outpatient E/M service claims use the same CPT® codes, comparison across these services without imposing further assumptions on the data is possible.

Finally, I note that office/outpatient E/M service claims represent the highest levels of telehealth usage in the medical claims data. Table 1 shows that the frequency of telehealth usage in office/outpatient E/M service claims vastly outweighs telehealth usage for other CPT® codes where comparison across visit modalities is possible.

Table 1: 10 Highest Telehealth Usage CPT® Codes, 2018q1-2022q1

CPT® Code	Type of Service	Visit Count
1. **99213**	**E/M Service**	6,492,604
2. **99214**	**E/M Service**	5,885,303
3. 90837	Psychotherapy	2,458,440
4. 90834	Psychotherapy	2,313,999
5. **99212**	**E/M Service**	868,421
6. 99442	Telephone E/M	660,510
7. 90833	Psychotherapy	560,020
8. **99215**	**E/M Service**	548,686
9. **99203**	**E/M Service**	413,335
10. 99443	Telephone E/M	396,760

Source: Optum's De-identified Clinformatics® Data Mart Database

3.2 Motivation

Before performing any formal analysis, I first use the medical claims data to describe how telehealth usage changed over time, from the beginning of 2018 to 2022. The evolution in telemedicine services before and during the COVID-19 pandemic will serve as important context for the analysis to come.

First, I trace the counts of total monthly office/outpatient E/M service claims by face-to-face ($F2F$) or telehealth (TH) visit modality between 2018 and 2022 in Figure 1. Additionally, I show trends in overall visit counts by either modality with the dashed line in Figure 1. Prior to the COVID-19 pandemic, telehealth usage was extremely rare in these types of health care services. As the pandemic emerges, telehealth usage experiences a dramatic spike corresponding with a sharp decline in face-to-face usage in April 2020, although I note that the decline in face-to-face care is not entirely offset by telehealth usage. From the peak in April 2020 onward, telehealth usage declines but never returns to pre-pandemic norms, and we see a persistent use of telehealth into the beginning of 2022.

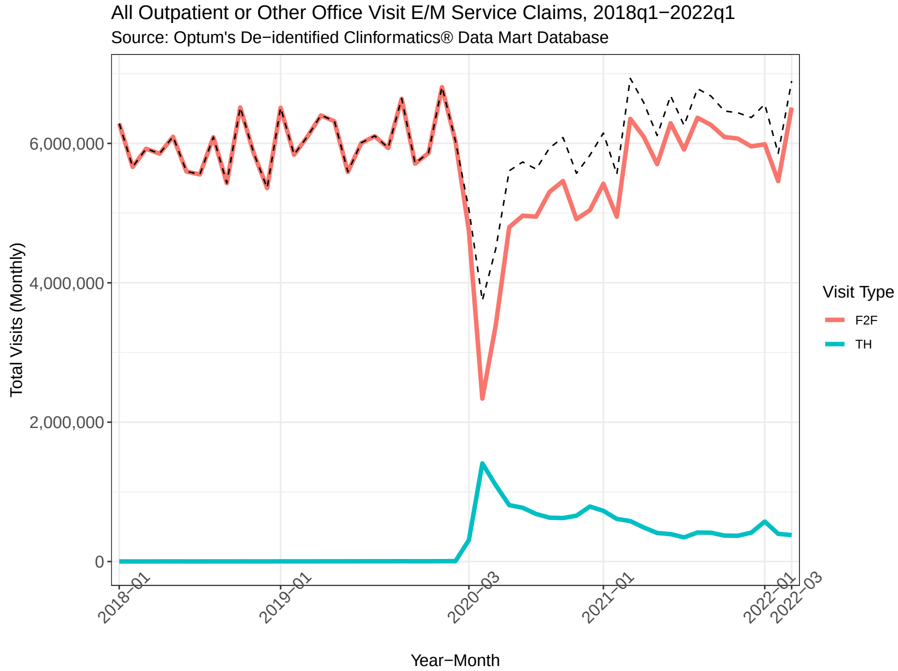


Figure 1: Telehealth vs. Face-to-Face Trends

Overall trends in use come from various types of patients and providers who may differ by purpose in telehealth usage and care background. In Appendix B, I explore trends in telehealth usage by several patient and provider categories, including established and new patients, patients with or without a referring provider, commercially insured and Medicare Advantage patients, and provider category of care. While certain patient and provider types outnumber others, trends in telehealth usage generally reflect the trends shown in Figure 1, albeit at different scales of health care utilization.

Given the national health emergency response to the global COVID-19 pandemic, we may also consider how these trends were impacted by those with a COVID-19 diagnosis at the time of a claim versus those without. Non-COVID-19 claims are the vast majority of the claims observed and reflect the main trends in Figure 1. For the claims associated with a COVID-19 diagnosis, most visits are conducted using a face-to-face visit modality rather than telehealth. COVID-19-related claims and telehealth versus face-to-face modality trends are depicted in Figure C16 in the appendix.[5]

With respect to provider trends in telehealth usage, I also examine how telehealth usage evolved by provider state of operation. In April 2019, one year prior to the COVID-19 lockdowns, telehealth visits were less than 0.5% of all monthly visits in almost every U.S. state. In April 2020, some states saw telehealth usage higher than 50% of all monthly visits, with the highest usage rates in the Northeastern U.S. region. By the following April, telehealth usage rates had declined, and into 2022, telehealth was a lower but nontrivial number of monthly visits across states. This evolution in provider telehealth usage across states is shown in detail in Figure A3 in the appendix.

[5] More detail about identifying COVID-19 diagnoses in the data over time can be found alongside the robustness checks and discussion in Appendix C.

Finally, it may be possible that certain health care providers specialized in telehealth usage while other providers never used telehealth at all, such that impacts of telehealth are concentrated in a subset of providers and not primarily driven by differences in modality. However, I find that while the overall distribution of provider-specific telehealth usage as a share of monthly health care provision returns to pre-pandemic levels, providers are more likely to have integrated at least some level of telehealth services into their mixture of services after March 2020. Box-and-whisker plots for the distribution of telehealth frequencies by individual provider in month-year cohorts, as well as the trends of individual providers who use telehealth services as discrete shares of monthly services, are shown in Figure 2.

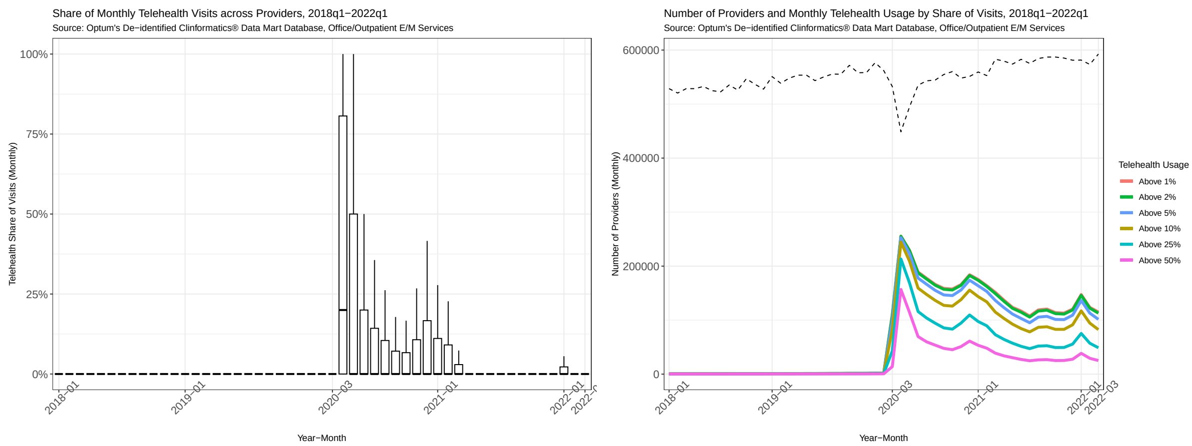


Figure 2: Telehealth Trends by Provider

While it is certainly the case that there are providers with little use of telemedicine in provision of care, Figure 2 shows that the landscape of telehealth usage was permanently altered after March 2020. Although many providers have no telehealth usage in their monthly provision of care one year from the onset of the COVID-19 pandemic, approximately one out of every six providers use telehealth at least once a month, and one out of every twelve providers use telehealth 25 percent of the time. This post-March 2020 shift in provider variation in telehealth usage suggests that visit modality appears to be a key decision in the provision of health care services.

All in all, the rise in telehealth usage during the COVID-19 pandemic was a widespread phenomenon. Even after the initial peak in April 2020, telehealth usage persists above pre-pandemic levels. While there is observed variation across patient and provider heterogeneity to account for in the empirical strategy to follow, the data tells a story suggesting that the changes in visit modality are not driven by individual patient or provider characteristics of reduced dimension. In the next section, I detail the empirical strategy used to study the impact of telehealth usage during this time period and how I incorporate the theoretical framework to estimate physician information costs.

4 Empirical Framework

With the theory, data, and motivation outlined, I turn to defining the empirical framework used in the estimation strategy to follow. First, I introduce a series of reduced-form models estimated at the encounter, patient, and provider levels of analysis and identification assumptions for this strategy. Next, I describe a series of alternative approaches to address potential threats to validity in my primary empirical strategy. Finally, I revisit the rational inattention model first described in Section 2 and present a calibration method to estimate information costs across visit modalities.

4.1 Reduced-Form Models

I first employ a series of reduced-form models to study the impact of telehealth usage on severe health outcomes. I use three different levels of analysis: observations of each encounter, patient, and provider. Additionally, I use two different forms of severe health outcomes: patient mortality and patient ER visit within 6 months of an office/outpatient E/M service claim.[6] For brevity, I will include both forms of severe health outcomes in the model specifications that I introduce below, although impacts on these outcomes are estimated separately.

First, I estimate the encounter-level (or claim-level) reduced-form model using logistic regression. With F representing the logistic CDF, the model takes the form

$$\begin{aligned}\mathbb{P}(1^{\text{SevHlthaft6}}_{e,ijt}|\mathbf{X}_{e,ijt}) = F(\beta_0 &+ \beta_1 1^{\text{Telehealth}}_{e,ijt} + \beta_2 1^{\text{COVID}}_{e,ijt} + \beta_3 \text{Age}_{it} + \beta_4 \text{CCI}_{it} \\ &+ \gamma_{\text{Race}_i} + \gamma_{\text{Gender}_i} + \gamma_{\text{State}_j} + \gamma_{\text{CPT Code}_e})\end{aligned} \tag{12}$$

for encounter e, patient i, and provider j at date t for all $t \in T_c$ and $\forall T_c \in \mathbb{T}$. Each T_c represents a cohort of claims with respect to a given month and year, where t can be any day of the month within month-year cohort T_c. I estimate this model for each month-year cohort T_c in $\mathbb{T}$, which spans January 2018 to September 2021, the last month-year cohort with a full 6-month window of severe health outcomes observed.

The dependent variable $1^{\text{SevHlthaft6}}_{e,ijt}$ is an indicator variable taking the value of 1 if patient i experienced a severe health outcome, measured by a death or ER claim within 6 months after encounter e. The key variable of interest $1^{\text{Telehealth}}_{e,ijt}$ takes the value of 1 if telehealth is the visit modality used for encounter e. I also include a set of variables controlling for health factors that may also contribute to severe health outcomes. $1^{\text{COVID}}_{e,ijt}$ is an independent variable that flags when a COVID-19 diagnosis is associated with encounter e, and Age_{it} and CCI_{it} control for age (in years) and Charlson Comorbidity Index of patient i at time t.[7] I incorporate fixed effects for patient race and gender, provider state of operation, and CPT® code associated with encounter

[6]Patient date of death is directly observable in the data. For ER claims, I filter the data for claims with revenue codes from 0450 through 0459 and link using anonymized patient identifiers.

[7]To construct Charlson Comorbidity Index measures for each patient, I follow the algorithm outlined by Quan et al. (2005) for ICD-10 diagnosis codes using a four-quarter look-back period. More information on identifying COVID-19 diagnoses can be found in the appendix.

e, and I cluster standard errors at the provider state level.[8]

Next, I aggregate encounter-level observations up to the level of each patient i in month-year cohort T_c and use a similar reduced-form model as in Equation 12, where instead we have

$$\begin{aligned}\mathbb{P}(1^{\text{SevHlthaft6}}_{iT_c}|\mathbf{X}_{iT_c}) =& F(\beta_0 + \beta_1 \text{Telehealth}_{iT_c} + \beta_2 \text{COVID}_{iT_c} + \beta_3 \text{Visit Count}_{iT_c} \\ &+ \beta_4 \text{Age}_{iT_c} + \beta_5 \text{CCI}_{iT_c} + \gamma_{\text{Race}_i} + \gamma_{\text{Gender}_i} + \gamma_{\text{State}_i} + \gamma_{\text{CPT Code}_i})\end{aligned} \tag{13}$$

for patient i and for all month-years $T_c \in \mathbb{T}$. Here, the dependent variable $1^{\text{SevHlthaft6}}_{e,ijt}$ remains the same, as well as the logistic CDF represented by F.

As a result of the aggregation, Telehealth_{iT_c} and COVID_{iT_c} represent the share of patient i's encounters in month-year T_c that use telehealth as a visit modality and are associated with a COVID-19 diagnosis, respectively. To control for levels of monthly health care utilization at the patient level, I include a new term $\text{Visit Count}_{iT_c}$ that captures the total number of office/outpatient E/M service claims for patient i in month-year T_c. The average age and CCI of patient i and modal values for race, gender, provider state, and CPT® code in T_c are used in this specification. As before, standard errors are clustered at the provider state level.

The final level of aggregation I use is a provider-level reduced-form model. In this specification, I aggregate to each provider j in month-year T_c either by encounter e or patient i. Using Poisson quasi-maximum likelihood estimation, I estimate the model

$$\begin{aligned}&\log(\mathbb{E}(\text{SevHlthRate}_{jT_c}|\mathbf{X}_{jT_c})) = \beta_0 + \beta_1 \text{Telehealth}_{jT_c} + \beta_2 \text{COVID}_{jT_c} + \beta_3 \text{Age}_{jT_c} + \beta_4 \text{CCI}_{jT_c} \\ &+ \beta_5 \text{Non-White}_{jT_c} + \beta_6 \text{Male}_{jT_c} + \beta_7 \text{Referred}_{jT_c} + \beta_8 \text{Medicare}_{jT_c} + \gamma_{\text{State}_j} + \gamma_{\text{CPT Code}_j} + \varepsilon_{jT_c}\end{aligned} \tag{14}$$

for provider j and for all month-years $T_c \in \mathbb{T}$. Here, $\text{SevHlthRate}_{jT_c}$ represents provider j's share of either encounters or patients in month-year T_c where patients experienced a severe health outcome, either death or ER claim, within 6 months. Independent variables Telehealth_{jT_c} and COVID_{jT_c} represent provider j's share of encounters or patients in month-year T_c that use telehealth and are associated with a COVID-19 diagnosis, respectively. Additional controls include mean patient age and CCI, as well as the share of encounters or patients where patients identify as a racial minority, are male, have a referring provider, or are Medicare Advantage plan members. As before, provider state of operation and CPT® code fixed effects are used and standard errors are clustered at the provider state level.

4.1.1 Identification

The desired objective from an empirical approach is to identify and estimate the causal effect of telehealth usage in place of face-to-face care on severe health outcomes. In the ideal scenario, the following condition would hold:

$$(1^{\text{SevHlthaft6}}_1, 1^{\text{SevHlthaft6}}_0) \perp 1^{\text{Telehealth}}, \tag{15}$$

[8] A discussion of the appropriate level of clustering in this context can be found in the appendix.

or that potential severe health outcomes under each visit modality would be independent of assignment. This condition would hold in the case where the assignment to visit modality is random.

However, the process by which patients were either assigned to face-to-face or telehealth visit modality is not known from the data. As a result, I cannot assume that the condition in Equation 15 necessarily holds. In this context, there may instead be exposure to endogeneity in the treatment assignment, where visit modality may have been assigned based on factors leading up to the office/outpatient E/M service visit. As a result, estimation of the effect of telehealth usage may capture bias from a non-random selection process.

In the specifications presented, I consider the observable characteristics in the data that may have influenced visit modality assignment before and during the COVID-19 pandemic. Telehealth usage may have been dependent on patient health risk, patient demographics, or other details specific to the health care provider or service visit. In these reduced-form model specifications, observed covariates $\mathbf{X}$ include measures that capture these factors, and summary statistics on the composition of observed covariates can be found for each time cohort in the appendix. Under this approach, an assumption of conditional independence is made, which is that

$$(1_1^{\text{SevHlthaft6}}, 1_0^{\text{SevHlthaft6}}) \perp 1^{\text{Telehealth}} | \mathbf{X}. \tag{16}$$

This assumption implies that potential severe health outcomes under each visit modality ($1_1^{\text{SevHlthaft6}}$, $1_0^{\text{SevHlthaft6}}$) are unrelated to the observed visit modality $1^{\text{Telehealth}}$ conditional on observed covariates $\mathbf{X}$. By assuming Equation 16 holds, I use the model specifications to estimate the effect of telehealth usage on patient health outcomes.

Threats to the validity of this approach could come from a lack of balance or common support in covariates across visit modality assignment or from additional factors that induce telehealth usage not accounted for in the model specification. While covariates on patient health risk and demographics or on provider and visit details are used to isolate the effects of visit modality on severe health outcomes, it is possible that imbalance in these covariates across visit modality may be problematic for estimating treatment effects without bias. Additional factors could range from observed characteristics that were not selected as covariates for the model specification, such as reimbursement rates, to unobserved factors that are not included in the model specification or the data, such as unobserved patient health risk. Each of these types of threats could lead to a violation of the conditional independence assumption and cause bias.

In the following section, I provide a set of methods to address these threats. All in all, I find that performing the additional strategies lead to further support of the results from the empirical framework outlined in this section. The results obtained through the empirical framework outlined in this section are valuable in two main ways. First, these results will provide a justification for investigating the mechanism driving differences across visit modalities. Second, I will use these results paired with the closed-form representations derived from the theoretical model to estimate the information costs across visit modalities.

4.2 Alternative Approaches

To deal with potential threats to the validity of the primary empirical specification, I provide a series of alternative approaches and sensitivity analyses to reduce bias from confounding factors and potential treatment endogeneity. Toward improving balance, I estimate propensity scores of telehealth usage using observed covariates and then use a doubly robust estimation approach in alternative specifications. I further address the endogeneity in telehealth use with an instrumental variable that captures the (leave-one-out) medical provider's propensity to use telehealth as the visit modality. In this section, I detail the construction of propensity score weights and the instrumental variable, discussing the methods and necessary assumptions. Alongside these alternative approaches, in Appendix C, I perform additional sensitivity tests to investigate the validity of the main results and rule out the impact of additional factors on telehealth usage as visit modality and health outcomes.

4.2.1 Propensity Score Weighting

To improve balance across covariates in the main specification, I estimate propensity scores (Rosenbaum and Rubin (1983)) and then reweight observations using both inverse propensity score weights and overlap weights. Then, I estimate encounter- and patient-level analyses with weighted observations, and I use weighted aggregation to transform visit and patient observations to provider-level observations for provider-level analysis.

To construct propensity scores, I fit the model

$$\begin{aligned}\mathbb{P}(1^{\text{Telehealth}}_{e,ijt}|\mathbf{X}_{e,ijt}) = F(&\beta_0 + \beta_1 1^{\text{COVID}}_{e,ijt} + \beta_2 \text{Age}_{it} + \beta_3 \text{CCI}_{it} \\ &+ \gamma_{\text{Race}_i} + \gamma_{\text{Gender}_i} + \gamma_{\text{State}_j} + \gamma_{\text{CPT Code}_e})\end{aligned} \tag{17}$$

for encounter e, patient i, and provider j at date t for all $t \in T_q$ and $\forall T_q \in \mathbb{T}$, and with F representing the logistic CDF. Here, T_q represents each quarter between 2018q1 and 2022q1. With model fits for each quarter, I then construct the predicted values for each month-year cohort $T_c \subset T_q$ at either the encounter level or the patient level.

Using the propensity scores predicted for each encounter or patient observation, I construct two sets of weights, inverse propensity score weights and overlap weights. First, I construct inverse propensity score weights, a popular strategy used in observational studies in the medical and social sciences to reduce selection bias in estimation of treatment effects (Austin and Stuart (2015)). I obtain inverse propensity score weights according to the following formula:

$$IPW = \begin{cases} 1/PS & \text{when } 1^{\text{Telehealth}} = 1, \\ 1/(1-PS) & \text{when } 1^{\text{Telehealth}} = 0. \end{cases} \tag{18}$$

Here, PS is the predicted propensity score from the fitted model for each observation. The intuition is that observations in either visit modality are weighted more heavily when the propensity score is closer to matching the opposite modality. This can allow for a more appropriate comparison across telehealth and face-to-face observations.

I also employ a second method of propensity score weighting known as overlap weighting, as studied by Li et al. (2018). Overlap weighting handles extreme tails of the propensity score distribution by weighting observations more heavily in the center of the distribution than the extremes. I construct overlap weights using the following formula:

$$OLP = \begin{cases} 1 - PS & \text{when } 1^{\text{Telehealth}} = 1, \\ PS & \text{when } 1^{\text{Telehealth}} = 0. \end{cases} \tag{19}$$

With both sets of weights constructed, I follow a doubly robust estimation approach (Funk et al. (2011)) where estimation procedures following the main empirical framework proceed as usual except for the addition of either IPW or OLP weights. For provider-level analysis, IPW and OLP weights are used to aggregate observations either by visit or by patient. In this case, provider shares of visit-level or patient-level characteristics are constructed by weighted means. At all levels of analysis, covariates are used in the estimation procedure alongside weights. In Appendix Section C.1, I include figures comparing covariate balance across unweighted and weighted groups as well as propensity score distributions by telehealth usage to illustrate common support. While there is often pre-existing balance in covariates in the unweighted observations, both methods provide improvement in balance for analysis performed under the weighted specifications.

4.2.2 Instrumental Variable

To handle the potential endogeneity in telehealth use at the encounter level, I use an instrumental variable approach where the constructed instrument is the (leave-one-out) provider propensity to use telehealth as the visit modality. Using individual clinical propensity toward telehealth use is related to literature using judge leniency as an instrument for court decisions, such as in Kling (2006), Dahl et al. (2014), and Dobbie et al. (2018). In the context of telemedicine, Zeltzer et al. (2023) use physician adoption of telehealth as an instrument when examining increased access to telemedicine in the early lockdown phase of the COVID-19 pandemic in Israel. Intuitively, I wish to capture the effects of telehealth use through the channel of technological adoption and willingness to use telehealth at the medical practice level while simultaneously accounting for endogeneity threats from individual telehealth use at the encounter level.

I construct the leave-one-out provider propensity to use telehealth as

$$\text{IV}^{\text{ProvTHShare}}_{e,ijT_c} = \frac{\sum_{e',i',t' \in E_{jT_c}} 1^{\text{Telehealth}}_{e',i'jt'} - 1^{\text{Telehealth}}_{e,ijt}}{|E_{jT_c}| - 1} \tag{20}$$

for encounter e, patient i, provider j, at date t for all $t \in T_c$ and $\forall T_c \in \mathbb{T}$, where E_{jT_c} denotes the set of all office/outpatient E/M encounters serviced by provider j in the same state and with the same CPT® code as encounter e in month-year cohort T_c. Here, e', i', t' indexes each unique office/outpatient E/M encounter, patient, and date of service for provider j in month-year cohort T_c. Intuitively, this measure captures the tendency for a given medical professional to use telehealth as the visit modality across all (other) comparable encounters in each month.

Using the constructed instrument, I use two-stage least squares (2SLS) estimation to obtain the impact of telehealth use on likelihood of severe health outcomes.[9] In the first stage, I regress encounter-level telehealth use on leave-one-out provider telehealth propensity and all other observed covariates:

$$\begin{aligned}\mathbb{P}(1^{\text{Telehealth}}_{e,ijt}|\mathbf{Z}_{e,ijt}) = \pi_0 + \pi_1 \text{IV}^{\text{ProvTHShare}}_{e,ijT_c} + \pi_2 1^{\text{COVID}}_{e,ijt} + \pi_3 \text{Age}_{it} + \pi_4 \text{CCI}_{it} \\ + \gamma_{\text{Race}_i} + \gamma_{\text{Gender}_i} + \gamma_{\text{State}_j} + \gamma_{\text{CPT Code}_e} + \upsilon_{e,ijt}\end{aligned} \tag{21}$$

Then, in the second stage, I regress the occurrence of a death or ER visit within six months on the fitted telehealth use variable obtained in the first stage:

$$\begin{aligned}\mathbb{P}(1^{\text{SevHlthaft6}}_{e,ijt}|\mathbf{X}_{e,ijt}) = \beta_0 + \beta_1 \widehat{1^{\text{Telehealth}}_{e,ijt}} + \beta_2 1^{\text{COVID}}_{e,ijt} + \beta_3 \text{Age}_{it} + \beta_4 \text{CCI}_{it} \\ + \gamma_{\text{Race}_i} + \gamma_{\text{Gender}_i} + \gamma_{\text{State}_j} + \gamma_{\text{CPT Code}_e} + u_{e,ijt}\end{aligned} \tag{22}$$

For the leave-one-out provider propensity to use telehealth to be a valid instrument in this context, it must be established that the instrument is relevant and satisfies the exclusion restriction. For relevance, telehealth use at the encounter-level must be correlated with the individual provider's propensity to use telehealth for all other comparable services. To demonstrate this, I will present the results from the first stage estimation (following Equation 21) to show this assumption holds. For the exclusion restriction, a provider's propensity to use telehealth must only impact an individual's likelihood of severe health outcome after an encounter through the visit modality of telemedicine and must be independent of unobserved factors. While this assumption cannot be tested directly, the leave-one-out approach is intended to remove channels other than through telehealth use on the encounter by which provider propensity could impact subsequent health outcomes. Additionally, while it is unlikely that individual providers are randomly assigned to patients in this context, I assume that any individual provider's propensity to use telehealth is random from the patient's perspective, conditional on observed patient, provider, and visit characteristics.

If these assumptions on the validity of the instrument do not hold, then the instrumental variable approach may lead to biased estimates. In the event that the exclusion restriction does not hold, or if the instrument itself is correlated with observed and unobserved factors that influence health outcomes, then estimates from this approach may reflect bias. For instance, provider propensity may be imbalanced across observed patient, provider, or visit characteristics. Additionally, it is possible that unobserved patient factors, such as socioeconomic status (e.g., income, education, wealth), geographic status (e.g., distance to clinic, broadband access), or unmeasured health status (e.g., sudden health condition), are correlated with individual provider propensity to use telehealth during an encounter. While I cannot directly explore these relationships further in this data, the existing literature suggests that the socioeconomic and geographic inequalities traditionally associated with disparities in health outcomes have also been linked to disparities in telehealth access (e.g., Jaffe et al. (2020), Cantor et al. (2021), Rodriguez et al. (2021), Larson et al. (2022)). This implies that providers who demonstrate higher

[9] In Appendix C.2, I find little difference in results when using a logistic versus a linear model for the baseline specification; thus, I opt to use a 2SLS approach rather than a nonlinear IV approach.

degrees of telehealth adoption are likely to be in affluent areas where the distribution of patient demand reflects higher socioeconomic status levels. Therefore, if the instrument is correlated with the aforementioned unobserved factors, I expect that the resulting bias would lead to more conservative estimates of the impact of telehealth use on adverse health outcomes.

Furthermore, in Appendix C.2, I provide more detail on the balance and distribution of the instrument across observed patient, provider, and visit characteristics in the data. Balance across covariates largely reflect the balance in telehealth use at the encounter level, and the distribution of provider propensity to use telehealth reflects provider behavior as described in Section 3.2.

4.3 Model Calibration and Estimation

Using the rational inattention model detailed in Section 2, I combine the closed-form representations of attention strategies, information costs, and welfare with the reduced-form empirical results to calibrate the theoretical model and estimate the difference in information costs across visit modalities.

To compare visit modalities, I wish to obtain the relative and absolute change in physician information costs between one modality and another. I denote visit modality $M = F2F$ for face-to-face office/outpatient E/M service claims and $M = TH$ for claims using telehealth. The relative change in physician information costs can be represented as

$$\frac{\lambda_{TH} - \lambda_{F2F}}{\lambda_{F2F}} = \frac{\gamma_{TH} \times 2ra^2\sigma_x^2 - \gamma_{F2F} \times 2ra^2\sigma_x^2}{\gamma_{F2F} \times 2ra^2\sigma_x^2} = \frac{\gamma_{TH} - \gamma_{F2F}}{\gamma_{F2F}} \tag{23}$$

and the absolute change in physician information costs as

$$\frac{\lambda_{TH} - \lambda_{F2F}}{2ra^2\sigma_x^2} = \frac{\gamma_{TH} \times 2ra^2\sigma_x^2 - \gamma_{F2F} \times 2ra^2\sigma_x^2}{2ra^2\sigma_x^2} = \gamma_{TH} - \gamma_{F2F} \tag{24}$$

where $\lambda_M = \gamma_M \times 2ra^2\sigma_x^2$ for $M \in \{F2F, TH\}$.

The term of underlying model parameters $2ra^2\sigma_x^2$, which dictate the distribution of health status and stakes of diagnostic accuracy, is not directly observed and is difficult to identify or calibrate without strong assumptions on the data. However, by rewriting each λ_M in terms of γ_M for each visit modality M, I can calculate how information costs change across visit modalities without assuming arbitrary values for model parameters.

To obtain γ_{TH} and γ_{F2F} in Equations 23 and 24 from our empirical analysis, I rearrange Equation 6 in terms of γ_M to get

$$\frac{2 * V_M^*}{2ra^2\sigma_x^2} = \gamma_M \log_2(\gamma_M) - \gamma_M \text{ where } \gamma_M \in (0, 1] \; \forall M \in \{F2F, TH\}. \tag{25}$$

As discussed in detail previously, this relationship between indirect utility and information cost can be derived by assuming that $\gamma_M \in (0, 1]$ and that equilibrium attention ξ_M^* is nonzero. With respect to identification, there are three unknown terms in Equation 25: the value of indirect utility V_M^*, the share of information cost γ_M, and model parameters $2ra^2\sigma_x^2$. Additionally, since $\gamma_M \in (0, 1]$, the value on the right-hand side of Equation 25 is constrained as depicted in Figure 3, with the vertical line marking $\gamma_M = \exp(\ln(2) - 1)$.

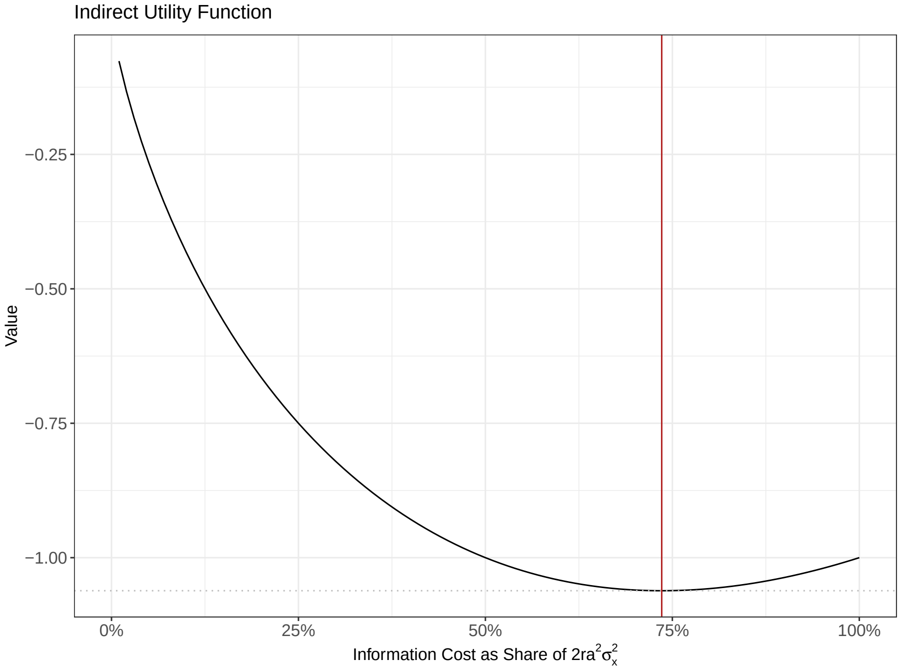


Figure 3: Information Cost and Indirect Utility

Thus, in order to obtain γ_M from Equation 25 using the data, I set

$$\hat{V_M^*} = -\frac{2 * V_M^*}{2ra^2\sigma_x^2} \ \forall M \in \{F2F, TH\}. \tag{26}$$

where $\hat{V_M^*}$ is a physician's observed rate of severe health outcomes within 6 months of the unit of observation (either encounter or patient) under visit modality M. Doing so is advantageous for a few reasons. First, instead of assuming V_M^* is observed directly, I assume that the data allows me to observe $\hat{V_M^*}$ such that model parameters $2ra^2\sigma_x^2$ do not have to be separately identified or calibrated. Second, this measure from the data is physician-specific, allowing for a measure of welfare that is congruent with the model. Third, the rate of severe health outcomes observed per unit of observation is naturally constrained between 0 and 1, such that $-\hat{V_M^*}$ fits the range of values of indirect utility for $\gamma_M \in (0, 1]$. While a rate has positive range, using the additive inverse of the rate to match the range of the model leads to an interpretation of increased severe health outcomes as costly, which fits the context.

To obtain unique values of γ_M for each $\hat{V_M^*}$ using Equation 26, I assume that $\frac{\partial V_M^*}{\partial \gamma_M} < 0$, which is equivalent to assuming that $\gamma_M \in (0, \exp(\ln(2) - 1)]$, the condition in Equation 11. By assuming increased information costs are always welfare-decreasing, I also assume that lower rates of severe health outcomes come from lower information costs, and vice versa. To justify this assumption, I reason that the existence of an observed visit between physician and patient in the claims data implies moderate to high attention strategies for physicians. On the other hand, I assume that physician-patient interactions that may be characterized by low attention strategies where the condition in Equation 11 is violated do not result in a formal visit and therefore are simply not observed in the claims data.

Following this assumption, I can estimate γ_{F2F} and γ_{TH} from Equation 25, which will allow us to evaluate changes in information costs represented by Equations 23 and 24. With the empirical framework set forth, we move to the discussion of the estimation results.

5 Results

In this section, I discuss the results of the estimation procedures corresponding to the empirical framework detailed in Section 4, including reduced-form estimation, alternative approaches, and calculation of information costs through model calibration.

5.1 Reduced-Form Estimation

Reduced-form results from logistic regression analysis at encounter and patient levels indicate that telehealth usage is associated with increased likelihood of severe health outcomes within 6 months of an office/outpatient E/M service claim, including both mortality and ER visits as measures. Provider-level reduced-form results show additional evidence that higher rates of telehealth usage induce higher rates of severe health outcomes within either a provider's set of monthly encounters or patients. Results below are estimated and reported separately for each month-year cohort T_c and for each measure of severe health outcome. While date of death is used to check for mortality within 6 months of encounter, I only look for the presence of at least one ER visit within 6 months of encounter. In this way, estimates should be seen as a conservative lower bound on overall emergency room utilization associated with telehealth usage.

Figure 4 displays the encounter-level reduced-form estimation results for the impact of telehealth usage on likelihood of either death or ER visit within 6 months following the office/outpatient E/M service. Average marginal effects are reported for each month-year cohort between 2018q1 and 2021q3, along with 95% confidence intervals and a vertical dashed line representing March 2020. For both measures, the results indicate increasing likelihood of severe health outcome in almost every month-year cohort. With respect to mortality, the post-March 2020 mean average marginal effect across month-year cohorts is approximately 4.4 additional deaths per 1,000 encounters. For ER visits, this number is approximately 13.0 additional ER visits per 1,000 encounters.

Prior to March 2020, I also find average marginal effects estimated across cohorts suggesting that telehealth usage is associated with higher likelihood of death and ER visit within 6 months. However, due to the low frequency of telehealth usage during this time period relative to the overall number of office/outpatient E/M services, these estimates are very noisy, and the 95% confidence intervals occasionally overlap with zero. Additionally, the onset of the COVID-19 pandemic brought changes in regulations and norms regarding telehealth usage and care

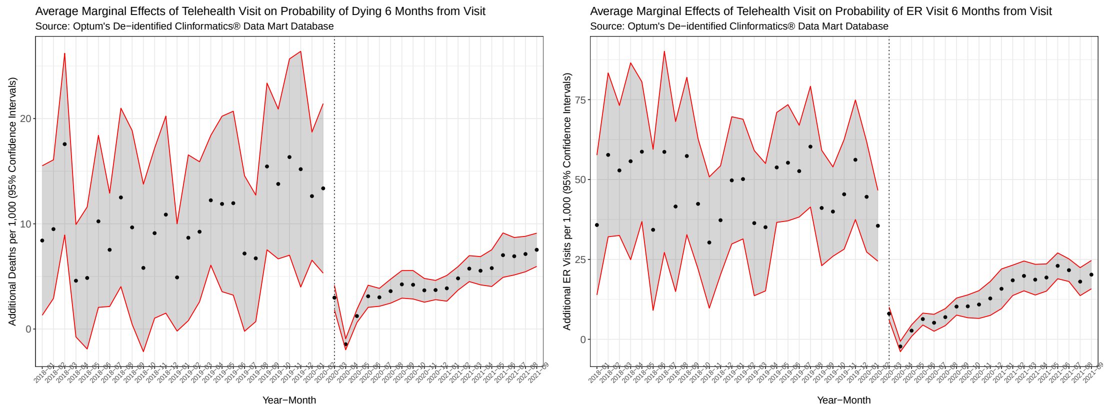


Figure 4: Encounter-Level Reduced-Form Estimation Results

delivery, so comparing these two periods as similar could be problematic. Given these caveats, it is nevertheless telling that we find positive association between telehealth and severe health outcomes in the pre-pandemic period also.

I highlight here that the primary exception to the results in Figure 4 are in April 2020, at the height of the COVID-19 lockdowns in the United States. This exception persists at patient and provider levels as well. To understand this, it is paramount to consider April 2020 with distinction from most cohorts in this time period. Given the level of caution that came with the onset of the COVID-19 pandemic, April 2020 likely represents an unusual cohort of patients and providers with unique behaviors across both modalities that contribute to this result. Nevertheless, for conservative estimates of impact, I group April 2020 in with other month-year cohorts to understand telehealth usage across post-March 2020 cohorts.

In addition to the main results in Figure 4, I examine the differential impacts of telehealth usage across patient and provider type. In Appendix B, I explore results for patient sorted by commercial and Medicare Advantage insurance plan members, referred and non-referred patients, and established and new patients, as well as providers by provider category, whether primary care, specialty, or non-physician professional. These results are included in the appendix and are included for encounter and patient levels of analysis. I find that marginal effects are strongest in patient populations of Medicare Advantage members, patients who do not have a referring provider, and patients who are established. For provider category, impacts of telehealth usage are largely similar to the main results. Any differences that are observed across patients and providers in telehealth and face-to-face encounters are correlated with underlying health status, and since severe health outcomes are functions of latent variables, thresholds for these outcomes are more likely to be met if patients are categorically less healthy.

Moving toward the patient-level reduced-form estimation results, we may wonder if encounters leading to severe health outcomes within 6 months are driven by a subset of unhealthy patients who are contributing to a high degree of health care utilization. By aggregating encounter-level observations to patient and month-year cohort levels, as well as including visit counts as a covariate, I control for health care utilization. Nevertheless, I find a similar result at the patient level, as shown in Figure 5.

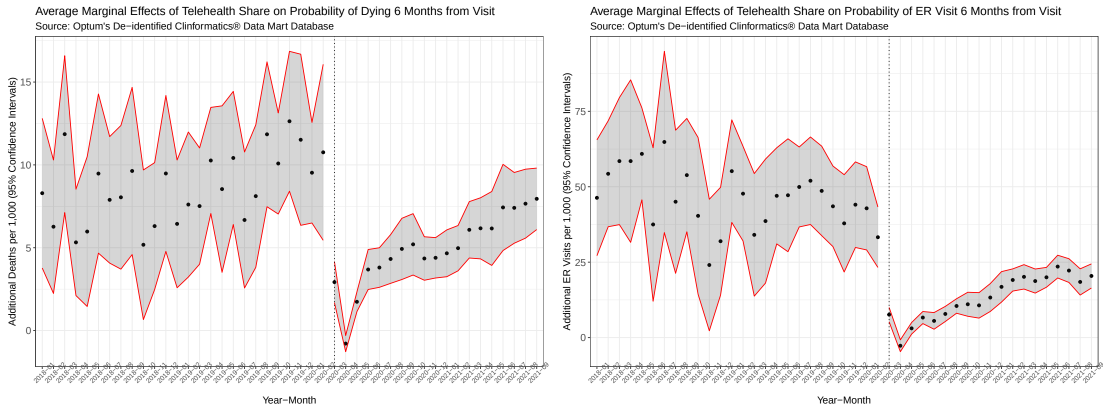


Figure 5: Patient-Level Reduced-Form Estimation Results

At the patient level, telehealth usage contributes to a post-March 2020 mean average marginal effect of 4.9 additional deaths and 13.3 additional ER visits per 1,000 patients. Just as before, these approximations do not include pre-pandemic estimates, but cohorts before March 2020 exhibit positive and less precise associations between telehealth usage and severe health outcomes. Additionally, April 2020 remains an exception, suggesting telehealth usage contributed to fewer severe health outcomes within 6 months for this cohort. Overall, however, patient-level estimates reinforce encounter-level results, which suggest higher likelihood of severe health outcomes associated with telehealth usage.

Finally, Figures 6 and 7 display provider-level reduced-form estimation results for each month-year cohort and for each severe health outcome measure. Estimates from the Poisson quasi-maximum likelihood estimation process are displayed as percent changes in provider-specific encounter or patient rates of severe health outcomes. Figure 6 displays estimates of percent change for mortality and ER visit rates when provider rates are aggregated by encounter, and Figure 7 displays estimates when aggregated by patient.

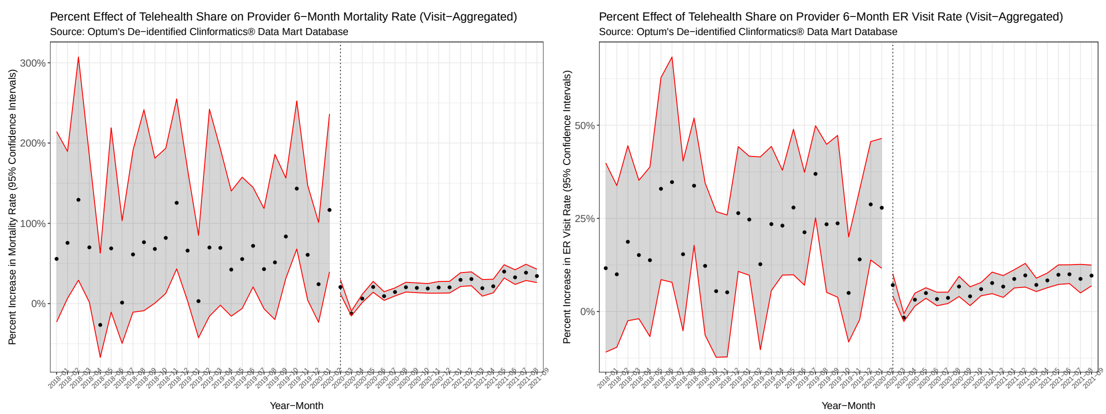


Figure 6: Provider-Level Reduced-Form Estimation Results, Aggregated by Encounter

These provider-level findings reinforce the results at the encounter and patient levels. The post-March 2020 mean percent change in provider 6-month mortality rate as a result of telehealth usage when visit-aggregated is approximately 21 percent; when aggregated by patient, mean percent change is approximately 24 percent across cohorts. For provider 6-month ER

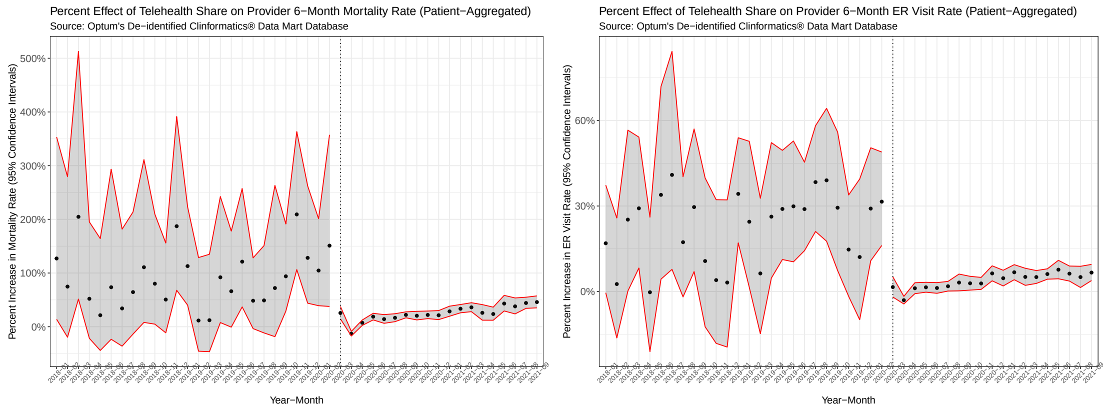


Figure 7: Provider-Level Reduced-Form Estimation Results, Aggregated by Patient

visit rates, the post-March 2020 mean percent change from telehealth usage is 6 percent when visit-aggregated and 4 percent when patient-aggregated. The discrepancy in percent change between measures of severe health outcomes can be traced back to the underlying rates of these phenomena; the mortality rate per visit or patient across providers is much lower than the rate of any ER visit within 6 months. Previously noted impacts on pre-pandemic and April 2020 cohorts continue to remain relevant in the provider-level cases.

5.2 Alternative Results

To complement the primary findings, I display results for the alternative approaches detailed in Section 4.2.

First, I obtain results from alternative specifications where propensity scores are constructed and used in to weight observations as described in Section 4.2.1. Table 2 below provides a comparison of post-March 2020 mean average marginal effects for all levels of analysis across unweighted and weighted strategies. The results from the alternative specifications with propensity score weighting are similar in magnitude to the baseline results (shown as the unweighted results), with a small increase in estimated effects and percent changes when death is used as the outcome measure and decrease when ER visit is used. Full estimation results are displayed in Appendix Section C.1.

Next, I show the results from the instrumental variable approach, where I employ provider propensity to use telehealth as an instrument for encounter-level telehealth use in a two-stage least squares estimation. To illustrate the relevance of the instrument, Figure 8 displays the first-stage results. Shown in the figure is the estimated association of the leave-one-out provider propensity to use telehealth with actual telehealth used during the encounter and associated 95% confidence intervals, as well as the first-stage F-test results. The instrument is strongly associated with the treatment across all months in the data, and the high first-stage F-test results across all months further reflect the strength of the instrumental variable.

With the relevance of the instrument established, I present the results of the second-stage estimation. Figure 9 shows the encounter-level estimation results for the impact of fitted tele-

Table 2: Post-March 2020 Mean Impacts, Unweighted and Weighted

Severe Health Outcome	Level	Measure	Unweighted	*IPW*	*OLP*
Death (6-Month)	Encounter	AME	4.4	4.8	4.4
ER Visit (6-Month)	Encounter	AME	13.0	12.8	12.4
Death (6-Month)	Patient	AME	4.9	5.5	5.2
ER Visit (6-Month)	Patient	AME	13.3	10.7	10.2
Death Rate (6-Month)	Provider (by Visit)	% Δ	21%	24%	25%
ER Visit Rate (6-Month)	Provider (by Visit)	% Δ	6%	5%	5%
Death Rate (6-Month)	Provider (by Patient)	% Δ	24%	28%	29%
ER Visit Rate (6-Month)	Provider (by Patient)	% Δ	4%	2%	2%

Note: AMEs are reported per 1,000 encounters or patients based on level of analysis. Provider visit rates are either aggregated by all monthly visits or patients of a provider.
Source: Optum's De-identified Clinformatics® Data Mart Database

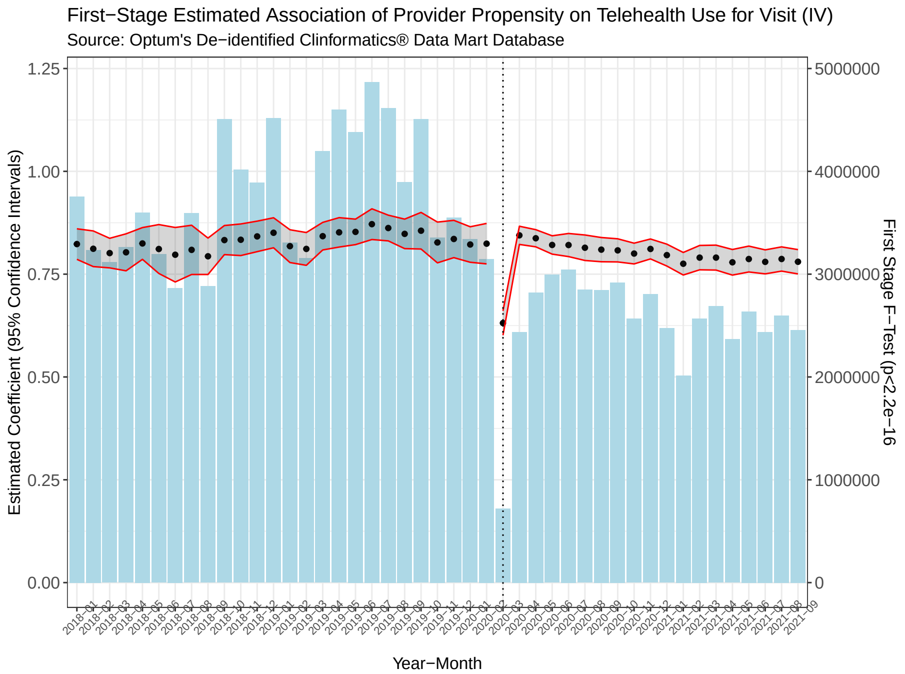


Figure 8: First-Stage Results

health use from the first stage on likelihood of death and ER visit within 6 months of the office/oupatient E/M encounter. Through this approach, I find decreased support for impact on likelihood of severe health outcome in six months with death as the outcome in the post-March 2020 period, with a mean average marginal effect of 0.02 additional deaths per 1,000 encounters. For the typical month in the post-March 2020 period, I also note that the estimated average marginal effects are not statistically significant, where confidence intervals often overlap with zero. On the other hand, I find increased support with ER visit as the outcome in this period, with a mean average marginal effect of 18.9 additional ER visits per 1,000 encounters. Estimated average marginal effects are higher in the typical month than in the baseline results.

To summarize, the inverse propensity score weighting approach improves balance across observed factors in telehealth use, and the results from this strategy reflect a slight decrease in the typical effect of telehealth use on likelihood of ER visit and a slight increase in the

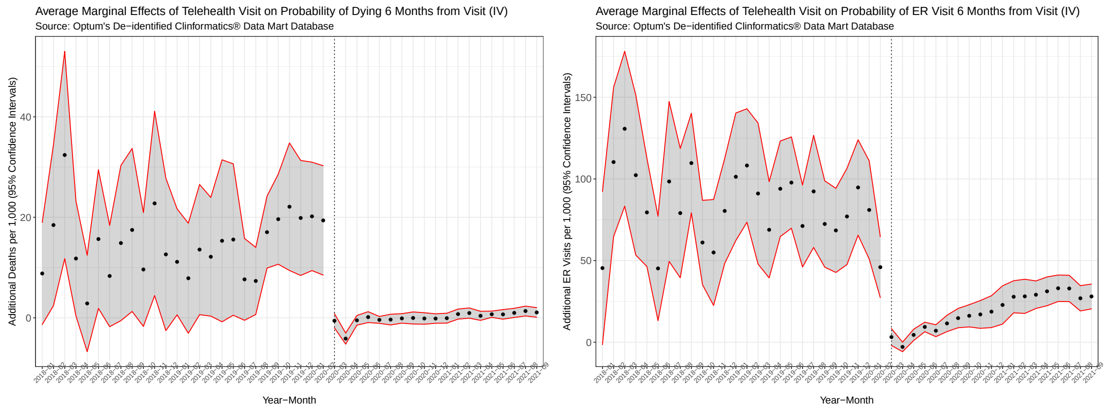


Figure 9: Encounter-Level 2SLS Estimation Results

effects on likelihood of death. For the instrumental variable approach, where the potential endogeneity in telehealth use is addressed through a two-stage least squares estimation with a leave-one-out provider telehealth propensity measure as the instrument, we find weaker support for death as the adverse health outcome and stronger support for ER visit relative to the baseline results. While there is variation in the degree of support for the impacts estimated in the main specification, I ultimately find strong evidence of impact of telehealth use on increased likelihood of subsequent adverse health outcome within six months after providing alternative approaches to address endogeneity and confounding. In Appendices B and C, I include additional details from the main specification and alternative approaches, as well as sensitivity tests to further establish robustness of the results.

All in all, the evidence suggesting telehealth usage is associated with higher likelihood and rates of severe health outcomes lead us to consider the mechanisms driving this result. As outlined in Section 2, the rational inattention model allows us to view these differences as a result of differences in information costs across visit modalities. In order to estimate how much information costs change across modalities, I move to our model calibration and calculation of information costs.

5.3 Estimation of Information Costs

To estimate changes in information costs across visit modalities according to Section 4.3, I obtain $\hat{V_M^*}$ in Equation 26 using physician 6-month mortality rates and ER visit rates, aggregated either by visit and by patient, following an office/outpatient E/M service claim. Then, using Equation 25, I estimate γ_{F2F} and γ_{TH}. To obtain cohort-level representation of changes in information costs between telehealth and face-to-face modalities, I use provider-level reduced-form results in Section 5.1 to acquire month-year estimates for severe health outcome rates and average marginal effects of telehealth usage, which I then use to calculate values of γ_{F2F} and γ_{TH} representative for each cohort of physicians. Because these reduced-form estimates are conditional on patient, provider, and encounter characteristics, they are consistent with the ceteris paribus assumption across visit modalities in the rational inattention model.

Figures 10 through 11 display trends for relative change in physician information costs for each measure of severe health outcome. The average post-March 2020 percent increase in information costs is 25.271% [16.737%, 34.445%] when visit-aggregated and 29.435% [18.777%, 41.108%] when patient-aggregated using 6-month mortality rates. For 6-month ER visit rates, the average percent increase is 8.453% [5.414%, 11.586%] when visit-aggregated and 4.917% [1.758%, 8.180%] when patient-aggregated. These differences are an artifact of the baseline differences in frequency of mortality and ER visits within 6 months of office/outpatient E/M service claims. Pre-pandemic information costs for telehealth usage are certainly high, but much like in the reduced-form empirical analysis that preceded this section, these estimates are less precise, and the 95% confidence intervals frequently overlap with zero, indicative of a different context of telehealth usage. From March 2020 onward, except for April 2020, however, I see a consistent, nonzero percent increase in physician information costs.

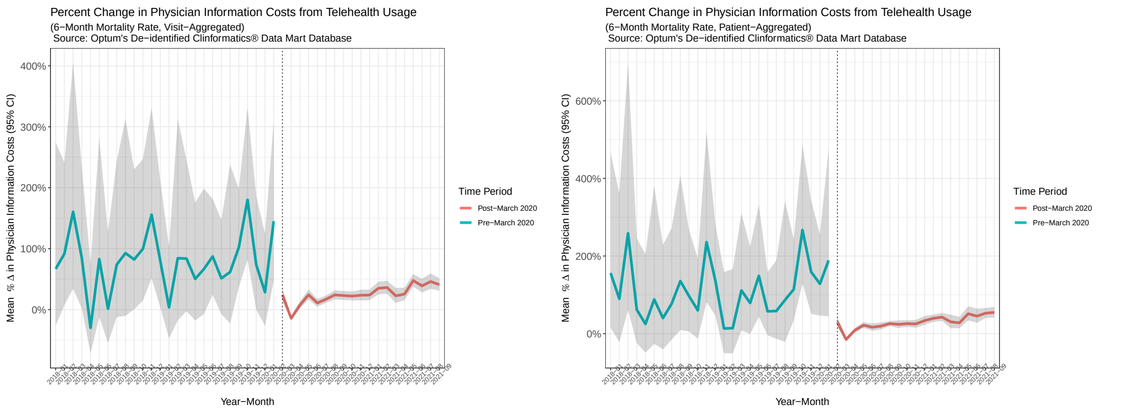


Figure 10: Percent Change in Information Costs, by Mortality Rate

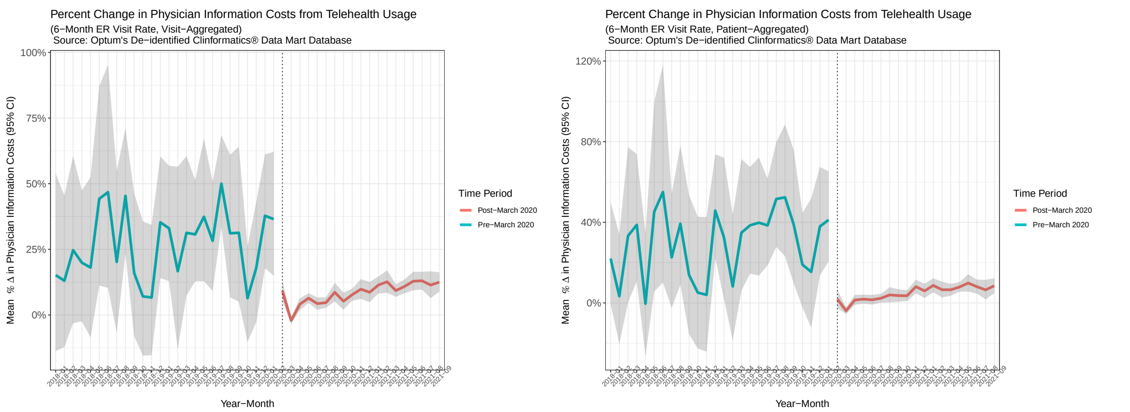


Figure 11: Percent Change in Information Costs, by ER Visit Rate

The absolute change in physician information costs across measures of severe health outcomes show similar trends, with the caveat that results are scaled by underlying model parameters. In these cases, the additional increases in information costs estimated by ER visit rates are larger in magnitude than for mortality rates, which align with the difference in estimates for relative change. Here, it is sufficient to present the trends in percent change as a result of difference in visit modality; by doing so, this allow us to remain agnostic on the values of the unobserved model parameters. Trends in absolute change are reported in Appendix A.[10]

[10] I also include cohort-level rates of provider 6-month mortality and ER visit aggregated by visit and

As a result of increased rates of severe health outcomes at the provider level, our model estimates tell us that average physician information costs increase between 5 to 29 percent when using telehealth as a visit modality, relative to face-to-face visits.

6 Summary and Concluding Remarks

The COVID-19 pandemic brought a surge in telehealth and telemedicine delivery as an alternative to face-to-face care. While playing a crucial part of health care delivery at the height of pandemic lockdowns, we must work to answer what role telehealth will have in our health care systems into the future. This paper works to address this broad concern by studying the evolution of telehealth alongside face-to-face care in office/outpatient evaluation and management service claims, where telehealth usage is substitutable for in-person care and has the highest frequency relative to other comparable claims.

Using medical claims and diagnosis data paired with patient and provider information from a nationwide private health insurance claims database, I characterize how telehealth usage evolved from two years before to two years after the onset of the COVID-19 pandemic, exploring trends across patient types, provider states of operation, and as a share of overall visits over time. I link this rise in telehealth with patient health outcomes and show that increased telehealth usage is associated with higher likelihood of mortality and ER visits within 6 months at encounter, patient, and provider levels. To explain these results, I introduce a rational inattention model to the physician-patient interaction that provides a mechanism for explaining these differences across visit modalities as a difference in information costs. With this model, I estimate the difference in information costs across visit modalities.

This paper is limited in the sense that the claims data I use does not cover how patients and providers decide which visit modality to use for a given office/outpatient E/M service claim. This is an unfortunate limitation present in current data sources that allow the study of impacts of telehealth usage at a large scale. Alongside the alternative empirical approaches shown to combat potential endogeneity concerns, I include additional sensitivity analyses and robustness checks in the appendix. Future work that studies the ground-level process for selecting visit modality as well as the specific characteristics of visit modalities that contribute to higher or lower information costs will be important for understanding the full picture of telehealth usage and its impacts.

As we work toward a better knowledge of telehealth and telemedicine and its effects in health care, future work should continue to link socioeconomic and geographic heterogeneity to telehealth uptake and resulting health outcomes. This research agenda should also include investigating how post-March 2020 telehealth usage in other contexts of care, whether substituting or complementing in-person services, impacts patient health outcomes as well as providers. As technological advancements and increases in knowledge improve how visit modalities are administered, future work must continue to document the dynamics of telehealth and its impacts. Additionally, future studies that incorporate costly information acquisition into contexts

patient in Appendix A.

of health care will help identify how information frictions influence various types of health-related decision-making. Building the literature in each of these dimensions will provide a greater understanding of our health care systems as a whole.

References

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. M. (2022). When Should You Adjust Standard Errors for Clustering?*. *The Quarterly Journal of Economics*. qjac038.

Abaluck, J. and Gruber, J. (2011). Choice inconsistencies among the elderly: Evidence from plan choice in the medicare part d program. *American Economic Review*, 101(4):1180–1210.

Armaignac, D. L., Saxena, A., Rubens, M., Valle, C. A., Williams, L.-M. S., Veledar, E., and Gidel, L. T. (2018). Impact of telemedicine on mortality, length of stay, and cost among patients in progressive care units: Experience from a large healthcare system. *Critical Care Medicine*, 46:728–735.

Austin, P. C. and Stuart, E. A. (2015). Moving towards best practice when using inverse probability of treatment weighting (iptw) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in Medicine*, 34(28):3661–3679.

Bajowala, S. S., Milosch, J., and Bansal, C. (2020). Telemedicine Pays: Billing and Coding Update. *Curr Allergy Asthma Rep*, 20(10):60.

Bhatia, R. S., Chu, C., Pang, A., Tadrous, M., Stamenova, V., and Cram, P. (2021). Virtual care use before and during the COVID-19 pandemic: a repeated cross-sectional study. *CMAJ Open*, 9(1):E107–E114.

Bose, S., Dun, C., Zhang, G. Q., Walsh, C., Makary, M. A., and Hicks, C. W. (2022). Medicare beneficiaries in disadvantaged neighborhoods increased telemedicine use during the covid-19 pandemic. *Health Affairs*, 41(5):635–642. PMID: 35500186.

Brotman, J. and Kotloff, R. (2021). Providing outpatient telehealth services in the united states: Before and during coronavirus disease 2019. *Chest*, 159(4):1548–1558.

Brown, Z. Y. and Jeon, J. (2021). Product proliferation under rational inattention: Application to health insurance. *AEA Papers and Proceedings*, 111:554–59.

Brown, Z. Y. and Jeon, J. (2023). Endogenous information and simplifying insurance choice. *Working Paper*.

Busso, M., Gonzalez, M. P., and Scartascini, C. (2022). On the demand for telemedicine: Evidence from the covid-19 pandemic. *Health Economics*, 31(7):1491–1505.

Cantor, J. H., McBain, R. K., Pera, M. F., Bravata, D. M., and Whaley, C. M. (2021). Who Is (and Is Not) Receiving Telemedicine Care During the COVID-19 Pandemic. *Am J Prev Med*, 61(3):434–438.

Caplin, A. and Dean, M. (2015). Revealed preference, rational inattention, and costly information acquisition. *American Economic Review*, 105(7):2183–2203.

Choi, N. G., DiNitto, D. M., Marti, C. N., and Choi, B. Y. (2022). Telehealth use among older adults during covid-19: Associations with sociodemographic and health characteristics, technology device ownership, and technology learning. *Journal of Applied Gerontology*, 41(3):600–609. PMID: 34608821.

Cover, T. M. and Thomas, J. A. (2006). *Elements of Information Theory (Wiley Series in Telecommunications and Signal Processing)*. Wiley-Interscience, USA.

Dahl, G. B., Kostøl, A. R., and Mogstad, M. (2014). Family Welfare Cultures *. *The Quarterly Journal of Economics*, 129(4):1711–1752.

Dobbie, W., Goldin, J., and Yang, C. S. (2018). The effects of pretrial detention on conviction, future crime, and employment: Evidence from randomly assigned judges. *American Economic Review*, 108(2):201–40.

Ekeland, A. G., Bowes, A., and Flottorp, S. (2010). Effectiveness of telemedicine: A systematic review of reviews. *International Journal of Medical Informatics*, 79(11):736–771.

Funk, M. J., Westreich, D., Wiesen, C., rmer, T., Brookhart, M. A., and Davidian, M. (2011). Doubly robust estimation of causal effects. *Am J Epidemiol*, 173(7):761–767.

Handel, B. R. and Kolstad, J. T. (2015). Health insurance for "humans": Information frictions, plan choice, and consumer welfare. *American Economic Review*, 105(8):2449–2500.

Handel, B. R., Kolstad, J. T., and Spinnewijn, J. (2019). Information Frictions and Adverse Selection: Policy Interventions in Health Insurance Markets. *The Review of Economics and Statistics*, 101(2):326–340.

Jaffe, D. H., Lee, L., Huynh, S., and Haskell, T. P. (2020). Health inequalities in the use of telehealth in the united states in the lens of covid-19. *Population Health Management*, 23(5):368–377. PMID: 32816644.

Kling, J. R. (2006). Incarceration length, employment, and earnings. *American Economic Review*, 96(3):863–876.

Kling, J. R., Mullainathan, S., Shafir, E., Vermeulen, L. C., and Wrobel, M. V. (2012). Comparison friction: experimental evidence from medicare drug plans. *Quarterly Journal of Economics*, 127(1):199–235.

Larson, A. E., Zahnd, W. E., Davis, M. M., Stange, K. C., Yoon, J., Heintzman, J. D., and Harvey, S. M. (2022). Before and During Pandemic Telemedicine Use: An Analysis of Rural and Urban Safety-Net Clinics. *Am J Prev Med*, 63(6):1031–1036.

Lee, B., Zhao, W., Yang, K. C., Ahn, Y. Y., and Perry, B. L. (2021). Systematic Evaluation of State Policy Interventions Targeting the US Opioid Epidemic, 2007-2018. *JAMA Netw Open*, 4(2):e2036687.

Li, F., Thomas, L. E., and Li, F. (2018). Addressing Extreme Propensity Scores via the Overlap Weights. *American Journal of Epidemiology*, 188(1):250–257.

Matějka, F. and McKay, A. (2015). Rational inattention to discrete choices: A new foundation for the multinomial logit model. *American Economic Review*, 105(1):272–98.

Maćkowiak, B., Matějka, F., and Wiederholt, M. (2021). Rational inattention: a review. Working Paper Series 2570, European Central Bank.

Maćkowiak, B. and Wiederholt, M. (2009). Optimal sticky prices under rational inattention. *American Economic Review*, 99(3):769–803.

Nittari, G., Savva, D., Tomassoni, D., Tayebati, S. K., and Amenta, F. (2022). Telemedicine in the covid-19 era: A narrative review based on current evidence. *International Journal of Environmental Research and Public Health*, 19(9).

Patel, S. Y., Mehrotra, A., Huskamp, H. A., Uscher-Pines, L., Ganguli, I., and Barnett, M. L. (2021a). Trends in Outpatient Care Delivery and Telemedicine During the COVID-19 Pandemic in the US. *JAMA Intern Med*, 181(3):388–391.

Patel, S. Y., Mehrotra, A., Huskamp, H. A., Uscher-Pines, L., Ganguli, I., and Barnett, M. L. (2021b). Variation in telemedicine use and outpatient care during the covid-19 pandemic in the united states. *Health Affairs*, 40(2):349–358. PMID: 33523745.

Quan, H., Sundararajan, V., Halfon, P., Fong, A., Burnand, B., Luthi, J. C., Saunders, L. D., Beck, C. A., Feasby, T. E., and Ghali, W. A. (2005). Coding algorithms for defining comorbidities in ICD-9-CM and ICD-10 administrative data. *Med Care*, 43(11):1130–1139.

Reed, M., Huang, J., Graetz, I., Muelly, E., Millman, A., and Lee, C. (2021). Treatment and Follow-up Care Associated With Patient-Scheduled Primary Care Telemedicine and In-Person Visits in a Large Integrated Health System. *JAMA Netw Open*, 4(11):e2132793.

Reges, O., Feldhamer, I., Wolff Sagy, Y., and Lavie, G. (2022). Factors Associated with Using Telemedicine in the Primary Care Clinics during the COVID-19 Pandemic in Israel. *Int J Environ Res Public Health*, 19(20).

Rodriguez, J. A., Betancourt, J. R., Sequist, T. D., and Ganguli, I. (2021). Differences in the use of telephone and video telemedicine visits during the COVID-19 pandemic. *Am J Manag Care*, 27(1):21–26.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Samson, L. W., Tarazi, W., Turrini, G., and Sheingold, S. (2021). Medicare beneficiaries' use of telehealth in 2020: Trends by beneficiary characteristics and location. *U.S. Department of Health and Human Services Office of the Assistant Secretary for Planning and Evaluation.*

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50(3):665–690. Swiss National Bank/Study Center Gerzensee Conference on Monetary Policy under Incomplete Information.

Sisk, B., Alexander, J., Bodnar, C., Curfman, A., Garber, K., McSwain, S. D., and Perrin, J. M. (2020). Pediatrician attitudes toward and experiences with telehealth use: Results from a national survey. *Academic Pediatrics*, 20(5):628–635.

Smith, A. C., Thomas, E., Snoswell, C. L., Haydon, H., Mehrotra, A., Clemensen, J., and Caffery, L. J. (2020). Telehealth for global emergencies: Implications for coronavirus disease 2019 (covid-19). *Journal of Telemedicine and Telecare*, 26(5):309–313. PMID: 32196391.

Snoswell, C. L., Chelberg, G., Guzman, K. R. D., Haydon, H. H., Thomas, E. E., Caffery, L. J., and Smith, A. C. (2021). The clinical effectiveness of telehealth: A systematic review of meta-analyses from 2010 to 2019. *Journal of Telemedicine and Telecare*, 0(0):1357633X211022907. PMID: 34184580.

Steventon, A., Ariti, C., Fisher, E., and Bardsley, M. (2016). Effect of telehealth on hospital utilisation and mortality in routine clinical practice: a matched control cohort study in an early adopter site. *BMJ Open*, 6.

Uscher-Pines, L. and Mehrotra, A. (2014). Analysis of teladoc use seems to indicate expanded access to care for patients without prior connection to a provider. *Health Affairs*, 33(2):258–264. PMID: 24493769.

Uscher-Pines, L., Sousa, J., Jones, M., Whaley, C., Perrone, C., McCullough, C., and Ober, A. J. (2021). Telehealth Use Among Safety-Net Organizations in California During the COVID-19 Pandemic. *JAMA*, 325(11):1106–1107.

Whaley, C. M., Ito, Y., Kolstad, J. T., Cowling, D. W., and Handel, B. (2022). The health plan environment in california contributed to differential use of telehealth during the covid-19 pandemic. *Health Affairs*, 41(12):1812–1820. PMID: 36469829.

Whaley, C. M., Pera, M. F., Cantor, J., Chang, J., Velasco, J., Hagg, H. K., Sood, N., and Bravata, D. M. (2020). Changes in Health Services Use Among Commercially Insured US Populations During the COVID-19 Pandemic. *JAMA Network Open*, 3(11):e2024984–e2024984.

Wiederholt, M. (2010). *Rational Inattention*, volume 4 of *The New Palgrave Dictionary of Economics*. Palgrave Macmillan.

Zeltzer, D., Einav, L., Rashba, J., and Balicer, R. D. (2023). The Impact of Increased Access to Telemedicine. *Journal of the European Economic Association*, 22(2):712–750.

Ziedan, E., Simon, K., and Wing, C. (2020). Effects of State COVID-19 Closure Policy on NON-COVID-19 Health Care Utilization. *NBER Working Paper*, (27621).

A Additional Figures and Tables

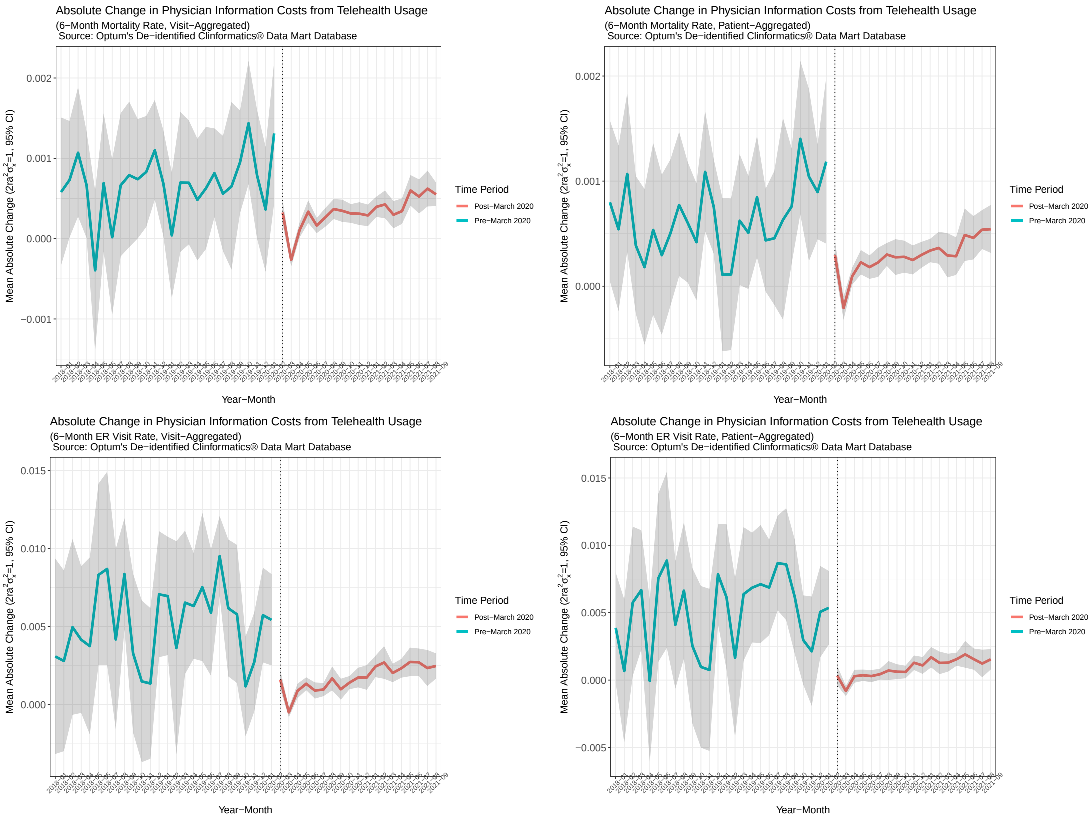


Figure A1: Absolute Change in Information Costs

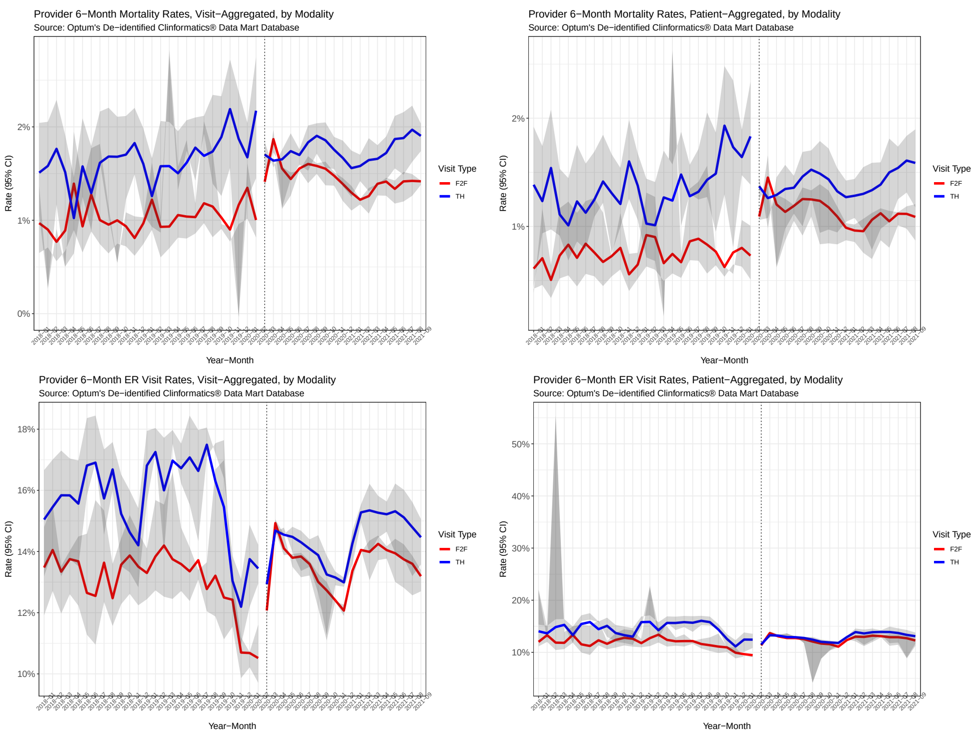
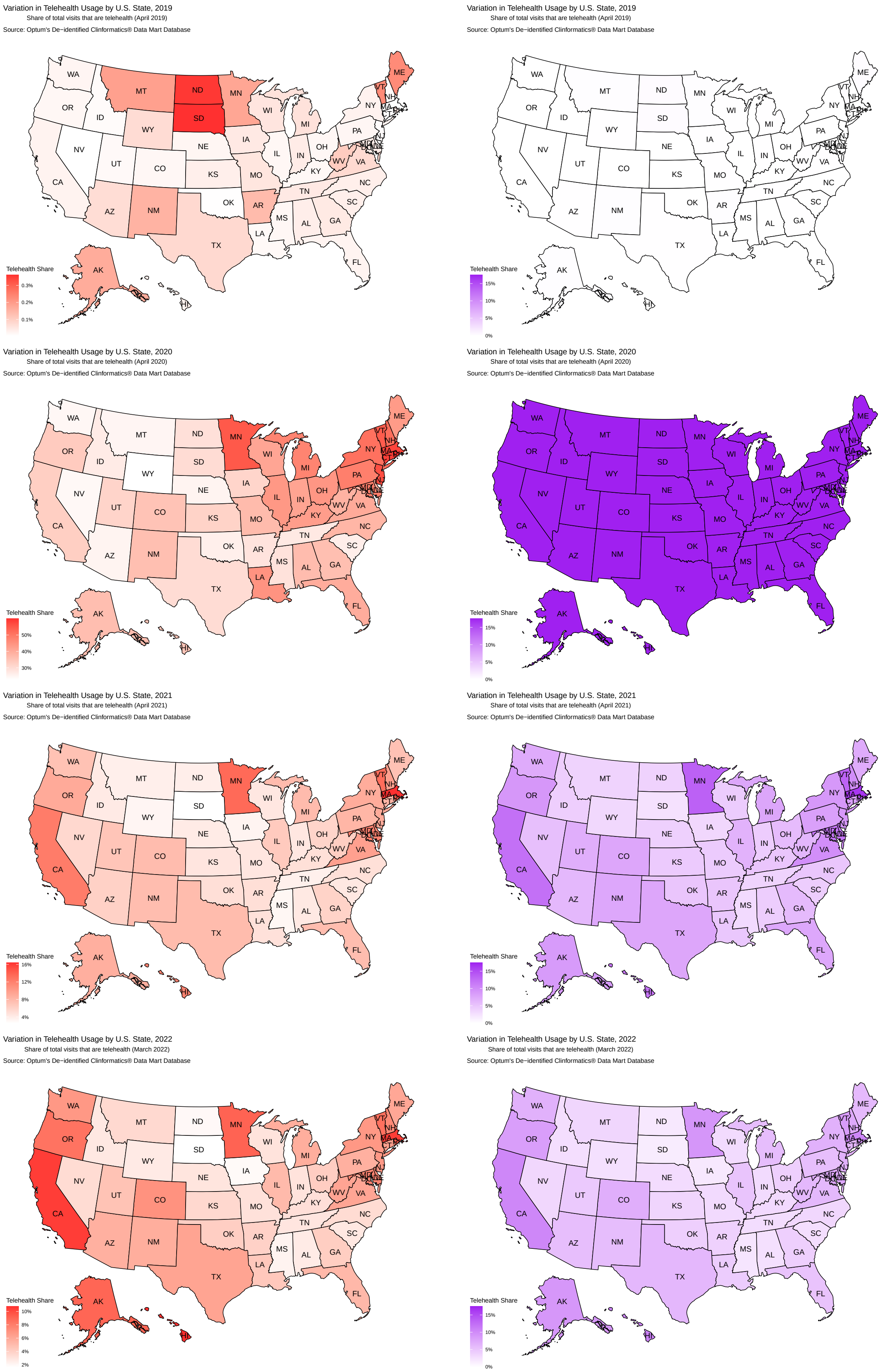


Figure A2: 6-Month Severe Health Outcome Rates, by Aggregation



(A) Differing Scales across Years (B) Same Scale across Years

Figure A3: Telehealth Trends by Provider State, 2019-2022

Table A1: Claim-Level Summary Statistics by Quarter, 2018

	2018q1	2018q2	2018q3	2018q4
	(N=15018808)	(N=16301231)	(N=15944612)	(N=16632877)
Telehealth				
0	15015028 (100.0%)	16296424 (100.0%)	15939673 (100.0%)	16626746 (100.0%)
1	3780 (0.0%)	4807 (0.0%)	4939 (0.0%)	6131 (0.0%)
COVID				
Mean (SD)	0 (0)	0 (0)	0 (0)	0 (0)
Median [Min, Max]	0 [0, 0]	0 [0, 0]	0 [0, 0]	0 [0, 0]
CCI				
Mean (SD)	1.73 (2.29)	1.75 (2.29)	1.81 (2.32)	1.79 (2.32)
Median [Min, Max]	1.00 [0, 21.0]	1.00 [0, 21.0]	1.00 [0, 20.0]	1.00 [0, 21.0]
Age				
Mean (SD)	57.8 (22.7)	59.0 (21.8)	59.1 (21.4)	57.9 (22.2)
Median [Min, Max]	65.0 [0, 90.0]	66.0 [0, 90.0]	66.0 [0, 90.0]	65.0 [0, 90.0]
Race				
A	549292 (3.7%)	568834 (3.5%)	550948 (3.5%)	580286 (3.5%)
B	1622781 (10.8%)	1728541 (10.6%)	1708767 (10.7%)	1730961 (10.4%)
H	1759594 (11.7%)	1821609 (11.2%)	1769305 (11.1%)	1813784 (10.9%)
W	10414384 (69.3%)	11205053 (68.7%)	10883621 (68.3%)	11291970 (67.9%)
Missing	672757 (4.5%)	977194 (6.0%)	1031971 (6.5%)	1215876 (7.3%)
Gender				
F	8670452 (57.7%)	9489306 (58.2%)	9284504 (58.2%)	9626434 (57.9%)
M	6347385 (42.3%)	6810997 (41.8%)	6659308 (41.8%)	7005709 (42.1%)
U	971 (0.0%)	928 (0.0%)	800 (0.0%)	734 (0.0%)
State				
AK	4144 (0.0%)	4594 (0.0%)	4591 (0.0%)	4475 (0.0%)
AL	276533 (1.8%)	302802 (1.9%)	320664 (2.0%)	321724 (1.9%)
AR	145070 (1.0%)	156337 (1.0%)	158179 (1.0%)	164693 (1.0%)
AZ	594856 (4.0%)	604242 (3.7%)	571985 (3.6%)	598174 (3.6%)
CA	1399447 (9.3%)	1439894 (8.8%)	1388167 (8.7%)	1411186 (8.5%)
CO	399137 (2.7%)	417912 (2.6%)	406361 (2.5%)	425429 (2.6%)
CT	152927 (1.0%)	258937 (1.6%)	254651 (1.6%)	274715 (1.7%)
DC	40502 (0.3%)	44249 (0.3%)	42929 (0.3%)	45266 (0.3%)
DE	16614 (0.1%)	19218 (0.1%)	18546 (0.1%)	19372 (0.1%)
FL	1545462 (10.3%)	1628458 (10.0%)	1582309 (9.9%)	1660123 (10.0%)
GA	829991 (5.5%)	860292 (5.3%)	912477 (5.7%)	906968 (5.5%)
HI	29250 (0.2%)	31959 (0.2%)	30775 (0.2%)	31235 (0.2%)
IA	156787 (1.0%)	168846 (1.0%)	166408 (1.0%)	176950 (1.1%)
ID	53413 (0.4%)	63303 (0.4%)	62993 (0.4%)	66954 (0.4%)
IL	540074 (3.6%)	618815 (3.8%)	598683 (3.8%)	617572 (3.7%)
IN	296857 (2.0%)	356587 (2.2%)	354806 (2.2%)	369578 (2.2%)
KS	84979 (0.6%)	89986 (0.6%)	88455 (0.6%)	93293 (0.6%)
KY	158071 (1.1%)	172500 (1.1%)	173417 (1.1%)	185849 (1.1%)
LA	143623 (1.0%)	150341 (0.9%)	148134 (0.9%)	157005 (0.9%)
MA	172551 (1.1%)	205990 (1.3%)	198968 (1.2%)	210680 (1.3%)
MD	251087 (1.7%)	263913 (1.6%)	248502 (1.6%)	259972 (1.6%)
ME	34810 (0.2%)	44651 (0.3%)	43828 (0.3%)	44877 (0.3%)
MI	114186 (0.8%)	124150 (0.8%)	119886 (0.8%)	125910 (0.8%)
MN	342566 (2.3%)	378291 (2.3%)	363402 (2.3%)	385658 (2.3%)
MO	401383 (2.7%)	432915 (2.7%)	429344 (2.7%)	441414 (2.7%)
MS	65564 (0.4%)	66285 (0.4%)	65540 (0.4%)	69482 (0.4%)
MT	12598 (0.1%)	13803 (0.1%)	13154 (0.1%)	13237 (0.1%)
NC	764590 (5.1%)	846590 (5.2%)	826269 (5.2%)	852197 (5.1%)
ND	43602 (0.3%)	47730 (0.3%)	48788 (0.3%)	47091 (0.3%)
NE	119523 (0.8%)	127277 (0.8%)	125270 (0.8%)	132987 (0.8%)
NH	39025 (0.3%)	49278 (0.3%)	49066 (0.3%)	50408 (0.3%)
NJ	348871 (2.3%)	383919 (2.4%)	369935 (2.3%)	396506 (2.4%)
NM	56548 (0.4%)	58027 (0.4%)	57026 (0.4%)	61415 (0.4%)
NV	92942 (0.6%)	104651 (0.6%)	105360 (0.7%)	111396 (0.7%)
NY	713928 (4.8%)	809122 (5.0%)	770273 (4.8%)	820066 (4.9%)
OH	440026 (2.9%)	505339 (3.1%)	502591 (3.2%)	530424 (3.2%)
OK	154543 (1.0%)	160816 (1.0%)	156694 (1.0%)	163685 (1.0%)
OR	154625 (1.0%)	172248 (1.1%)	161494 (1.0%)	169954 (1.0%)
PA	215119 (1.4%)	247445 (1.5%)	236073 (1.5%)	254300 (1.5%)
PR	1483 (0.0%)	1797 (0.0%)	1923 (0.0%)	1999 (0.0%)
RI	60899 (0.4%)	81169 (0.5%)	79076 (0.5%)	86086 (0.5%)
SC	298953 (2.0%)	317661 (1.9%)	314856 (2.0%)	333263 (2.0%)
SD	38308 (0.3%)	41192 (0.3%)	40049 (0.3%)	40814 (0.2%)
TN	266678 (1.8%)	288582 (1.8%)	291409 (1.8%)	299147 (1.8%)
TX	1750306 (11.7%)	1844102 (11.3%)	1793120 (11.2%)	1897212 (11.4%)
UN	34473 (0.2%)	36346 (0.2%)	35097 (0.2%)	35123 (0.2%)
UT	175650 (1.2%)	179633 (1.1%)	174486 (1.1%)	182796 (1.1%)
VA	268664 (1.8%)	293445 (1.8%)	283433 (1.8%)	302990 (1.8%)
VT	14069 (0.1%)	16854 (0.1%)	16761 (0.1%)	16703 (0.1%)
WA	254620 (1.7%)	277249 (1.7%)	264900 (1.7%)	276733 (1.7%)
WI	409852 (2.7%)	447461 (2.7%)	430977 (2.7%)	443882 (2.7%)
WV	24782 (0.2%)	29154 (0.2%)	29184 (0.2%)	30434 (0.2%)
WY	14247 (0.1%)	14874 (0.1%)	13348 (0.1%)	13475 (0.1%)
CPT Code				
99201	33584 (0.2%)	32416 (0.2%)	32202 (0.2%)	38185 (0.2%)
99202	248864 (1.7%)	264002 (1.6%)	267758 (1.7%)	260381 (1.6%)
99203	841829 (5.6%)	926033 (5.7%)	929130 (5.8%)	913479 (5.5%)
99204	606866 (4.0%)	681380 (4.2%)	680582 (4.3%)	674448 (4.1%)
99205	144390 (1.0%)	161646 (1.0%)	161122 (1.0%)	157938 (0.9%)
99211	196724 (1.3%)	213762 (1.3%)	207212 (1.3%)	206381 (1.2%)
99212	630143 (4.2%)	726900 (4.5%)	708848 (4.4%)	714407 (4.3%)
99213	6057071 (40.3%)	6455182 (39.6%)	6248017 (39.2%)	6613255 (39.8%)
99214	5765565 (38.4%)	6295378 (38.6%)	6177458 (38.7%)	6516068 (39.2%)
99215	493772 (3.3%)	544532 (3.3%)	532283 (3.3%)	538335 (3.2%)

Table A2: Claim-Level Summary Statistics by Quarter, 2019

	2019q1	2019q2	2019q3	2019q4
	(N=15880599)	(N=17124307)	(N=16933494)	(N=17159533)
Telehealth				
0	15873630 (100.0%)	17114943 (99.9%)	16922255 (99.9%)	17147457 (99.9%)
1	6969 (0.0%)	9364 (0.1%)	11239 (0.1%)	12076 (0.1%)
COVID				
Mean (SD)	0 (0)	0 (0)	0 (0)	0 (0)
Median [Min, Max]	0 [0, 0]	0 [0, 0]	0 [0, 0]	0 [0, 0]
CCI				
Mean (SD)	1.82 (2.35)	1.81 (2.34)	1.88 (2.38)	1.85 (2.37)
Median [Min, Max]	1.00 [0, 21.0]	1.00 [0, 22.0]	1.00 [0, 22.0]	1.00 [0, 22.0]
Age				
Mean (SD)	58.6 (22.4)	59.5 (21.7)	59.6 (21.4)	58.1 (22.3)
Median [Min, Max]	66.0 [0, 90.0]	66.0 [0, 90.0]	66.0 [0, 90.0]	65.0 [0, 90.0]
Race				
A	535928 (3.4%)	559431 (3.3%)	556018 (3.3%)	564756 (3.3%)
B	1710043 (10.8%)	1819229 (10.6%)	1810512 (10.7%)	1803181 (10.5%)
H	1753783 (11.0%)	1827112 (10.7%)	1849756 (10.9%)	1826117 (10.6%)
W	10711725 (67.5%)	11614722 (67.8%)	11465231 (67.7%)	11562131 (67.4%)
Missing	1169120 (7.4%)	1303813 (7.6%)	1251977 (7.4%)	1403348 (8.2%)
Gender				
F	9193564 (57.9%)	9973382 (58.2%)	9866555 (58.3%)	9947359 (58.0%)
M	6686461 (42.1%)	7150298 (41.8%)	7066329 (41.7%)	7211552 (42.0%)
U	574 (0.0%)	627 (0.0%)	610 (0.0%)	622 (0.0%)
State				
AK	4240 (0.0%)	4583 (0.0%)	4553 (0.0%)	4276 (0.0%)
AL	329900 (2.1%)	350289 (2.0%)	358044 (2.1%)	355887 (2.1%)
AR	161011 (1.0%)	175999 (1.0%)	176962 (1.0%)	179913 (1.0%)
AZ	590198 (3.7%)	644117 (3.8%)	622963 (3.7%)	607056 (3.5%)
CA	1371840 (8.6%)	1332101 (7.8%)	1339708 (7.9%)	1337043 (7.8%)
CO	410019 (2.6%)	439655 (2.6%)	427047 (2.5%)	382413 (2.2%)
CT	257417 (1.6%)	310293 (1.8%)	310211 (1.8%)	314742 (1.8%)
DC	44678 (0.3%)	49284 (0.3%)	49590 (0.3%)	52187 (0.3%)
DE	18819 (0.1%)	20453 (0.1%)	19992 (0.1%)	20538 (0.1%)
FL	1653107 (10.4%)	1761488 (10.3%)	1706635 (10.1%)	1771086 (10.3%)
GA	894985 (5.6%)	907674 (5.3%)	906656 (5.4%)	904355 (5.3%)
HI	29623 (0.2%)	31533 (0.2%)	31305 (0.2%)	30574 (0.2%)
IA	157976 (1.0%)	205851 (1.2%)	200524 (1.2%)	211252 (1.2%)
ID	64556 (0.4%)	72288 (0.4%)	71583 (0.4%)	72701 (0.4%)
IL	555403 (3.5%)	643530 (3.8%)	631976 (3.7%)	653084 (3.8%)
IN	338576 (2.1%)	380775 (2.2%)	379384 (2.2%)	383864 (2.2%)
KS	89535 (0.6%)	99484 (0.6%)	97645 (0.6%)	101125 (0.6%)
KY	180827 (1.1%)	192153 (1.1%)	192245 (1.1%)	196354 (1.1%)
LA	149976 (0.9%)	158462 (0.9%)	160685 (0.9%)	168180 (1.0%)
MA	199008 (1.3%)	222970 (1.3%)	214698 (1.3%)	218755 (1.3%)
MD	251643 (1.6%)	265291 (1.5%)	254992 (1.5%)	266021 (1.6%)
ME	41948 (0.3%)	52427 (0.3%)	51612 (0.3%)	49501 (0.3%)
MI	110848 (0.7%)	123302 (0.7%)	118179 (0.7%)	124811 (0.7%)
MN	310408 (2.0%)	365383 (2.1%)	361312 (2.1%)	379901 (2.2%)
MO	431786 (2.7%)	498437 (2.9%)	492377 (2.9%)	492849 (2.9%)
MS	69493 (0.4%)	67791 (0.4%)	68017 (0.4%)	69845 (0.4%)
MT	12478 (0.1%)	13765 (0.1%)	13129 (0.1%)	13042 (0.1%)
NC	874226 (5.5%)	901757 (5.3%)	897984 (5.3%)	910096 (5.3%)
ND	42336 (0.3%)	49484 (0.3%)	49517 (0.3%)	51409 (0.3%)
NE	124002 (0.8%)	137038 (0.8%)	135868 (0.8%)	144642 (0.8%)
NH	46942 (0.3%)	55524 (0.3%)	54485 (0.3%)	54502 (0.3%)
NJ	369074 (2.3%)	402174 (2.3%)	392336 (2.3%)	406287 (2.4%)
NM	63131 (0.4%)	73366 (0.4%)	72082 (0.4%)	73047 (0.4%)
NV	106498 (0.7%)	119142 (0.7%)	120632 (0.7%)	123626 (0.7%)
NY	704508 (4.4%)	802560 (4.7%)	769564 (4.5%)	785587 (4.6%)
OH	481862 (3.0%)	535984 (3.1%)	528054 (3.1%)	545701 (3.2%)
OK	157819 (1.0%)	170160 (1.0%)	168069 (1.0%)	153799 (0.9%)
OR	166247 (1.0%)	200195 (1.2%)	192321 (1.1%)	179062 (1.0%)
PA	239257 (1.5%)	275828 (1.6%)	267175 (1.6%)	274399 (1.6%)
PR	2051 (0.0%)	2312 (0.0%)	1933 (0.0%)	2021 (0.0%)
RI	83908 (0.5%)	90870 (0.5%)	87093 (0.5%)	89040 (0.5%)
SC	309442 (1.9%)	320040 (1.9%)	312455 (1.8%)	320362 (1.9%)
SD	35128 (0.2%)	41738 (0.2%)	40543 (0.2%)	40437 (0.2%)
TN	294592 (1.9%)	314664 (1.8%)	315890 (1.9%)	322683 (1.9%)
TX	1832273 (11.5%)	1879390 (11.0%)	1929612 (11.4%)	1983415 (11.6%)
UN	34048 (0.2%)	36298 (0.2%)	34123 (0.2%)	26871 (0.2%)
UT	175242 (1.1%)	182441 (1.1%)	180842 (1.1%)	185477 (1.1%)
VA	296453 (1.9%)	321502 (1.9%)	314992 (1.9%)	327107 (1.9%)
VT	15435 (0.1%)	18355 (0.1%)	18579 (0.1%)	18190 (0.1%)
WA	260622 (1.6%)	287650 (1.7%)	279905 (1.7%)	254457 (1.5%)
WI	391660 (2.5%)	465937 (2.7%)	457224 (2.7%)	474031 (2.8%)
WV	30646 (0.2%)	36587 (0.2%)	37104 (0.2%)	39045 (0.2%)
WY	12899 (0.1%)	13933 (0.1%)	13088 (0.1%)	12885 (0.1%)
CPT Code				
99201	46885 (0.3%)	44911 (0.3%)	45100 (0.3%)	59017 (0.3%)
99202	243948 (1.5%)	262997 (1.5%)	269327 (1.6%)	252182 (1.5%)
99203	899639 (5.7%)	986382 (5.8%)	1022324 (6.0%)	985643 (5.7%)
99204	674293 (4.2%)	744114 (4.3%)	780916 (4.6%)	773922 (4.5%)
99205	157027 (1.0%)	174285 (1.0%)	184116 (1.1%)	181005 (1.1%)
99211	181231 (1.1%)	192613 (1.1%)	193017 (1.1%)	189849 (1.1%)
99212	649040 (4.1%)	715608 (4.2%)	702294 (4.1%)	686205 (4.0%)
99213	6184333 (38.9%)	6613005 (38.6%)	6435918 (38.0%)	6619835 (38.6%)
99214	6313051 (39.8%)	6815831 (39.8%)	6729582 (39.7%)	6849135 (39.9%)
99215	531152 (3.3%)	574561 (3.4%)	570900 (3.4%)	562740 (3.3%)

Table A3: Claim-Level Summary Statistics by Quarter, 2020

	2020q1	2020q2	2020q3	2020q4
	(N=15139270)	(N=12903162)	(N=16214569)	(N=16493653)
Telehealth				
0	14873672 (98.2%)	9777356 (75.8%)	14249779 (87.9%)	14536999 (88.1%)
1	265598 (1.8%)	3125806 (24.2%)	1964790 (12.1%)	1956654 (11.9%)
COVID				
Mean (SD)	0.00283 (0.0531)	0.0310 (0.173)	0.0412 (0.199)	0.0760 (0.265)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
CCI				
Mean (SD)	1.89 (2.40)	1.91 (2.41)	1.87 (2.37)	1.85 (2.37)
Median [Min, Max]	1.00 [0, 22.0]	1.00 [0, 22.0]	1.00 [0, 23.0]	1.00 [0, 22.0]
Age				
Mean (SD)	58.9 (22.2)	60.1 (20.2)	60.3 (20.4)	59.2 (20.7)
Median [Min, Max]	66.0 [0, 90.0]	66.0 [0, 90.0]	66.0 [0, 90.0]	66.0 [0, 90.0]
Race				
A	472192 (3.1%)	357991 (2.8%)	497191 (3.1%)	524459 (3.2%)
B	1624144 (10.7%)	1451908 (11.3%)	1775175 (10.9%)	1774613 (10.8%)
H	1672623 (11.0%)	1386453 (10.7%)	1719178 (10.6%)	1772674 (10.7%)
W	10096470 (66.7%)	8715429 (67.5%)	10946989 (67.5%)	11033165 (66.9%)
Missing	1273841 (8.4%)	991381 (7.7%)	1276036 (7.9%)	1388742 (8.4%)
Gender				
F	8757014 (57.8%)	7496548 (58.1%)	9478061 (58.5%)	9611648 (58.3%)
M	6381733 (42.2%)	5406168 (41.9%)	6735864 (41.5%)	6881329 (41.7%)
U	523 (0.0%)	446 (0.0%)	644 (0.0%)	676 (0.0%)
State				
AK	3485 (0.0%)	2957 (0.0%)	3478 (0.0%)	3354 (0.0%)
AL	202908 (1.3%)	224319 (1.7%)	268674 (1.7%)	268881 (1.6%)
AR	166860 (1.1%)	154894 (1.2%)	187554 (1.2%)	190956 (1.2%)
AZ	600225 (4.0%)	523734 (4.1%)	609369 (3.8%)	639624 (3.9%)
CA	1166185 (7.7%)	879811 (6.8%)	1179836 (7.3%)	1222648 (7.4%)
CO	404941 (2.7%)	351649 (2.7%)	405373 (2.5%)	406413 (2.5%)
CT	280194 (1.9%)	231616 (1.8%)	315310 (1.9%)	311229 (1.9%)
DC	47004 (0.3%)	37616 (0.3%)	46706 (0.3%)	50537 (0.3%)
DE	17267 (0.1%)	13580 (0.1%)	17315 (0.1%)	17466 (0.1%)
FL	1600674 (10.6%)	1376523 (10.7%)	1605888 (9.9%)	1627051 (9.9%)
GA	812166 (5.4%)	702787 (5.4%)	855679 (5.3%)	853712 (5.2%)
HI	27525 (0.2%)	23368 (0.2%)	30434 (0.2%)	31414 (0.2%)
IA	159407 (1.1%)	131230 (1.0%)	170983 (1.1%)	172452 (1.0%)
ID	65066 (0.4%)	57803 (0.4%)	72440 (0.4%)	72545 (0.4%)
IL	548987 (3.6%)	455268 (3.5%)	613585 (3.8%)	618643 (3.8%)
IN	326932 (2.2%)	281606 (2.2%)	386626 (2.4%)	373862 (2.3%)
KS	86509 (0.6%)	77092 (0.6%)	95598 (0.6%)	96136 (0.6%)
KY	168368 (1.1%)	134218 (1.0%)	178411 (1.1%)	175093 (1.1%)
LA	136171 (0.9%)	109758 (0.9%)	131108 (0.8%)	135449 (0.8%)
MA	184441 (1.2%)	161243 (1.2%)	204006 (1.3%)	207309 (1.3%)
MD	238448 (1.6%)	180693 (1.4%)	231737 (1.4%)	240338 (1.5%)
ME	41838 (0.3%)	34130 (0.3%)	47251 (0.3%)	46125 (0.3%)
MI	102106 (0.7%)	79903 (0.6%)	105035 (0.6%)	104448 (0.6%)
MN	301348 (2.0%)	271835 (2.1%)	348984 (2.2%)	361423 (2.2%)
MO	441909 (2.9%)	373264 (2.9%)	473637 (2.9%)	456189 (2.8%)
MS	62595 (0.4%)	54053 (0.4%)	67056 (0.4%)	69534 (0.4%)
MT	11348 (0.1%)	9568 (0.1%)	12119 (0.1%)	12111 (0.1%)
NC	854835 (5.6%)	736344 (5.7%)	918086 (5.7%)	911655 (5.5%)
ND	44492 (0.3%)	39514 (0.3%)	49033 (0.3%)	48612 (0.3%)
NE	113525 (0.7%)	96901 (0.8%)	117796 (0.7%)	114665 (0.7%)
NH	44234 (0.3%)	39086 (0.3%)	53462 (0.3%)	53073 (0.3%)
NJ	349148 (2.3%)	281449 (2.2%)	378731 (2.3%)	392840 (2.4%)
NM	67443 (0.4%)	56116 (0.4%)	71477 (0.4%)	69588 (0.4%)
NV	111697 (0.7%)	93221 (0.7%)	127956 (0.8%)	135108 (0.8%)
NY	650924 (4.3%)	546491 (4.2%)	756748 (4.7%)	816010 (4.9%)
OH	460349 (3.0%)	399766 (3.1%)	521373 (3.2%)	520698 (3.2%)
OK	154092 (1.0%)	146727 (1.1%)	179716 (1.1%)	174126 (1.1%)
OR	175142 (1.2%)	160767 (1.2%)	202054 (1.2%)	209742 (1.3%)
PA	225470 (1.5%)	187055 (1.4%)	245170 (1.5%)	240831 (1.5%)
PR	1694 (0.0%)	1480 (0.0%)	1807 (0.0%)	1794 (0.0%)
RI	85105 (0.6%)	79442 (0.6%)	87465 (0.5%)	86572 (0.5%)
SC	287337 (1.9%)	258441 (2.0%)	309891 (1.9%)	307035 (1.9%)
SD	34226 (0.2%)	29868 (0.2%)	41009 (0.3%)	39733 (0.2%)
TN	288960 (1.9%)	260889 (2.0%)	317661 (2.0%)	319012 (1.9%)
TX	1803440 (11.9%)	1563722 (12.1%)	1853523 (11.4%)	1971239 (12.0%)
UN	30005 (0.2%)	16574 (0.1%)	21358 (0.1%)	21357 (0.1%)
UT	171102 (1.1%)	156750 (1.2%)	187361 (1.2%)	200430 (1.2%)
VA	286414 (1.9%)	235212 (1.8%)	297340 (1.8%)	301061 (1.8%)
VT	15263 (0.1%)	14519 (0.1%)	19302 (0.1%)	18048 (0.1%)
WA	234027 (1.5%)	199337 (1.5%)	265528 (1.6%)	265394 (1.6%)
WI	398593 (2.6%)	328588 (2.5%)	474149 (2.9%)	459166 (2.8%)
WV	35506 (0.2%)	31084 (0.2%)	40312 (0.2%)	39187 (0.2%)
WY	11340 (0.1%)	9301 (0.1%)	12069 (0.1%)	11735 (0.1%)
CPT Code				
99201	67854 (0.4%)	78082 (0.6%)	79268 (0.5%)	82693 (0.5%)
99202	226017 (1.5%)	198623 (1.5%)	286801 (1.8%)	322357 (2.0%)
99203	873431 (5.8%)	636618 (4.9%)	996083 (6.1%)	1019551 (6.2%)
99204	708881 (4.7%)	505700 (3.9%)	768957 (4.7%)	772568 (4.7%)
99205	167029 (1.1%)	123728 (1.0%)	179051 (1.1%)	176927 (1.1%)
99211	167220 (1.1%)	236034 (1.8%)	346721 (2.1%)	451685 (2.7%)
99212	588617 (3.9%)	640909 (5.0%)	709360 (4.4%)	742654 (4.5%)
99213	5749902 (38.0%)	5046609 (39.1%)	5955240 (36.7%)	6050578 (36.7%)
99214	6079783 (40.2%)	5021472 (38.9%)	6350275 (39.2%)	6332196 (38.4%)
99215	510536 (3.4%)	415387 (3.2%)	542813 (3.3%)	542444 (3.3%)

Table A4: Claim-Level Summary Statistics by Quarter, 2021-2022q1

	2021q1	2021q2	2021q3	2021q4	2022q1
	(N=15639709)	(N=18133114)	(N=18563758)	(N=18283614)	(N=16734252)
Telehealth					
0	14012023 (89.6%)	16911325 (93.3%)	17451994 (94.0%)	17183375 (94.0%)	15551167 (92.9%)
1	1627686 (10.4%)	1221789 (6.7%)	1111764 (6.0%)	1100239 (6.0%)	1183085 (7.1%)
COVID					
Mean (SD)	0.0674 (0.251)	0.0339 (0.181)	0.0573 (0.232)	0.0630 (0.243)	0.0629 (0.243)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
CCI					
Mean (SD)	1.88 (2.38)	1.84 (2.35)	1.90 (2.38)	1.89 (2.39)	1.97 (2.42)
Median [Min, Max]	1.00 [0, 23.0]	1.00 [0, 23.0]	1.00 [0, 23.0]	1.00 [0, 23.0]	1.00 [0, 23.0]
Age					
Mean (SD)	60.3 (20.8)	60.9 (20.8)	60.3 (21.1)	59.5 (21.6)	61.2 (21.0)
Median [Min, Max]	67.0 [0, 90.0]	67.0 [0, 90.0]	67.0 [0, 90.0]	66.0 [0, 90.0]	68.0 [0, 90.0]
Race					
A	483191 (3.1%)	546257 (3.0%)	568532 (3.1%)	566131 (3.1%)	490479 (2.9%)
B	1676220 (10.7%)	1912954 (10.5%)	1928800 (10.4%)	1854573 (10.1%)	1691036 (10.1%)
H	1690240 (10.8%)	1877446 (10.4%)	1900639 (10.2%)	1831796 (10.0%)	1670877 (10.0%)
W	10431293 (66.7%)	12047136 (66.4%)	12261765 (66.1%)	11998443 (65.6%)	11037740 (66.0%)
Missing	1358765 (8.7%)	1749321 (9.6%)	1904022 (10.3%)	2032671 (11.1%)	1844120 (11.0%)
Gender					
F	9060856 (57.9%)	10596667 (58.4%)	10813174 (58.2%)	10614874 (58.1%)	9704119 (58.0%)
M	6578148 (42.1%)	7535568 (41.6%)	7749660 (41.7%)	7667560 (41.9%)	7029027 (42.0%)
U	705 (0.0%)	879 (0.0%)	924 (0.0%)	1180 (0.0%)	1106 (0.0%)
State					
AK	3096 (0.0%)	3797 (0.0%)	3711 (0.0%)	3208 (0.0%)	3079 (0.0%)
AL	272521 (1.7%)	309398 (1.7%)	322476 (1.7%)	312040 (1.7%)	310763 (1.9%)
AR	174556 (1.1%)	212804 (1.2%)	219885 (1.2%)	211166 (1.2%)	194989 (1.2%)
AZ	670902 (4.3%)	716968 (4.0%)	683473 (3.7%)	630973 (3.5%)	583011 (3.5%)
CA	1145750 (7.3%)	1212758 (6.7%)	1256622 (6.8%)	1193249 (6.5%)	1088327 (6.5%)
CO	413140 (2.6%)	467575 (2.6%)	474050 (2.6%)	401078 (2.2%)	326378 (2.0%)
CT	308468 (2.0%)	373563 (2.1%)	383212 (2.1%)	387657 (2.1%)	356300 (2.1%)
DC	51068 (0.3%)	54515 (0.3%)	51582 (0.3%)	50551 (0.3%)	30679 (0.2%)
DE	17303 (0.1%)	29169 (0.2%)	31167 (0.2%)	31475 (0.2%)	29295 (0.2%)
FL	1661287 (10.6%)	1794441 (9.9%)	1764255 (9.5%)	1757202 (9.6%)	1677703 (10.0%)
GA	853831 (5.5%)	892290 (4.9%)	930564 (5.0%)	889462 (4.9%)	841126 (5.0%)
HI	30718 (0.2%)	34277 (0.2%)	34339 (0.2%)	32153 (0.2%)	27226 (0.2%)
IA	160123 (1.0%)	192987 (1.1%)	200250 (1.1%)	201170 (1.1%)	179993 (1.1%)
ID	72283 (0.5%)	87462 (0.5%)	90189 (0.5%)	86752 (0.5%)	81783 (0.5%)
IL	589860 (3.8%)	707680 (3.9%)	733024 (3.9%)	733810 (4.0%)	657200 (3.9%)
IN	369547 (2.4%)	454461 (2.5%)	469098 (2.5%)	449135 (2.5%)	406421 (2.4%)
KS	90390 (0.6%)	128708 (0.7%)	135469 (0.7%)	135693 (0.7%)	117079 (0.7%)
KY	164985 (1.1%)	187222 (1.0%)	200338 (1.1%)	199849 (1.1%)	181391 (1.1%)
LA	129120 (0.8%)	146434 (0.8%)	148843 (0.8%)	153905 (0.8%)	130580 (0.8%)
MA	204706 (1.3%)	248949 (1.4%)	254297 (1.4%)	260479 (1.4%)	236311 (1.4%)
MD	238320 (1.5%)	260340 (1.4%)	267029 (1.4%)	269054 (1.5%)	246513 (1.5%)
ME	44389 (0.3%)	55471 (0.3%)	57357 (0.3%)	54800 (0.3%)	47623 (0.3%)
MI	100194 (0.6%)	120105 (0.7%)	124028 (0.7%)	124133 (0.7%)	105006 (0.6%)
MN	308934 (2.0%)	367240 (2.0%)	374581 (2.0%)	390884 (2.1%)	344026 (2.1%)
MO	446685 (2.9%)	544277 (3.0%)	564029 (3.0%)	550604 (3.0%)	494195 (3.0%)
MS	65971 (0.4%)	82509 (0.5%)	91505 (0.5%)	86111 (0.5%)	78888 (0.5%)
MT	11672 (0.1%)	13886 (0.1%)	14511 (0.1%)	13239 (0.1%)	11760 (0.1%)
NC	653788 (4.2%)	748424 (4.1%)	782022 (4.2%)	757838 (4.1%)	710504 (4.2%)
ND	47810 (0.3%)	57547 (0.3%)	60092 (0.3%)	61252 (0.3%)	51346 (0.3%)
NE	105153 (0.7%)	125937 (0.7%)	131310 (0.7%)	132651 (0.7%)	115352 (0.7%)
NH	51489 (0.3%)	64650 (0.4%)	67044 (0.4%)	67287 (0.4%)	60338 (0.4%)
NJ	366614 (2.3%)	426882 (2.4%)	427180 (2.3%)	442872 (2.4%)	384959 (2.3%)
NM	73359 (0.5%)	95840 (0.5%)	98147 (0.5%)	93685 (0.5%)	88569 (0.5%)
NV	136438 (0.9%)	166209 (0.9%)	172198 (0.9%)	165443 (0.9%)	150215 (0.9%)
NY	715415 (4.6%)	818363 (4.5%)	804921 (4.3%)	831076 (4.5%)	707172 (4.2%)
OH	498504 (3.2%)	581938 (3.2%)	601702 (3.2%)	592276 (3.2%)	523591 (3.1%)
OK	163024 (1.0%)	218086 (1.2%)	224327 (1.2%)	191410 (1.0%)	189026 (1.1%)
OR	203766 (1.3%)	233565 (1.3%)	236640 (1.3%)	189935 (1.0%)	164061 (1.0%)
PA	231460 (1.5%)	291132 (1.6%)	299696 (1.6%)	300215 (1.6%)	267785 (1.6%)
PR	1699 (0.0%)	1918 (0.0%)	2046 (0.0%)	1972 (0.0%)	1668 (0.0%)
RI	74589 (0.5%)	87728 (0.5%)	87949 (0.5%)	87442 (0.5%)	84177 (0.5%)
SC	305209 (2.0%)	341037 (1.9%)	353195 (1.9%)	341221 (1.9%)	317307 (1.9%)
SD	39653 (0.3%)	52695 (0.3%)	55803 (0.3%)	55223 (0.3%)	51186 (0.3%)
TN	308901 (2.0%)	355990 (2.0%)	380687 (2.1%)	369029 (2.0%)	340498 (2.0%)
TX	1781032 (11.4%)	2282997 (12.6%)	2366056 (12.7%)	2283332 (12.5%)	2080926 (12.4%)
UN	18888 (0.1%)	25049 (0.1%)	33411 (0.2%)	241440 (1.3%)	327350 (2.0%)
UT	186018 (1.2%)	201473 (1.1%)	209309 (1.1%)	204590 (1.1%)	193746 (1.2%)
VA	292491 (1.9%)	339649 (1.9%)	350731 (1.9%)	349730 (1.9%)	316601 (1.9%)
VT	18101 (0.1%)	22396 (0.1%)	22906 (0.1%)	21966 (0.1%)	19970 (0.1%)
WA	263592 (1.7%)	308572 (1.7%)	310441 (1.7%)	272099 (1.5%)	232385 (1.4%)
WI	452861 (2.9%)	522013 (2.9%)	538001 (2.9%)	528155 (2.9%)	477683 (2.9%)
WV	39283 (0.3%)	51497 (0.3%)	55453 (0.3%)	79843 (0.4%)	79183 (0.5%)
WY	10753 (0.1%)	12241 (0.1%)	12607 (0.1%)	11800 (0.1%)	11009 (0.1%)
CPT Code					
99201	264 (0.0%)	193 (0.0%)	157 (0.0%)	92 (0.0%)	65 (0.0%)
99202	284567 (1.8%)	254568 (1.4%)	267080 (1.4%)	251538 (1.4%)	207054 (1.2%)
99203	878624 (5.6%)	1031297 (5.7%)	1093667 (5.9%)	1013847 (5.5%)	903509 (5.4%)
99204	879198 (5.6%)	1089900 (6.0%)	1110670 (6.0%)	1060506 (5.8%)	1015597 (6.1%)
99205	187134 (1.2%)	225500 (1.2%)	224889 (1.2%)	213797 (1.2%)	206709 (1.2%)
99211	352862 (2.3%)	308077 (1.7%)	403287 (2.2%)	434880 (2.4%)	360122 (2.2%)
99212	778558 (5.0%)	798623 (4.4%)	792154 (4.3%)	764458 (4.2%)	660785 (3.9%)
99213	5385390 (34.4%)	6254705 (34.5%)	6461103 (34.8%)	6419718 (35.1%)	5686002 (34.0%)
99214	6273819 (40.1%)	7436375 (41.0%)	7484440 (40.3%)	7409266 (40.5%)	6993934 (41.8%)
99215	619293 (4.0%)	733876 (4.0%)	726311 (3.9%)	715512 (3.9%)	700475 (4.2%)

Table A5: Patient-Level Summary Statistics by Quarter, 2018

	2018q1	2018q2	2018q3	2018q4
	(N=10312414)	(N=11109285)	(N=10893418)	(N=11383896)
Telehealth				
Mean (SD)	0.000252 (0.0147)	0.000294 (0.0159)	0.000315 (0.0165)	0.000377 (0.0181)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
COVID				
Mean (SD)	0 (0)	0 (0)	0 (0)	0 (0)
Median [Min, Max]	0 [0, 0]	0 [0, 0]	0 [0, 0]	0 [0, 0]
CCI				
Mean (SD)	1.49 (2.10)	1.50 (2.09)	1.55 (2.13)	1.53 (2.13)
Median [Min, Max]	1.00 [0, 21.0]	1.00 [0, 21.0]	1.00 [0, 20.0]	1.00 [0, 21.0]
Visit Count				
Mean (SD)	1.46 (0.863)	1.47 (0.877)	1.46 (0.878)	1.46 (0.872)
Median [Min, Max]	1.00 [1.00, 58.0]	1.00 [1.00, 100]	1.00 [1.00, 58.0]	1.00 [1.00, 52.0]
Age				
Mean (SD)	56.1 (23.2)	57.3 (22.4)	57.4 (22.1)	56.3 (22.8)
Median [Min, Max]	62.0 [0, 90.0]	64.0 [0, 90.0]	64.0 [0, 90.0]	63.0 [0, 90.0]
Race				
A	391029 (3.8%)	401059 (3.6%)	389349 (3.6%)	409391 (3.6%)
B	1104439 (10.7%)	1168503 (10.5%)	1146692 (10.5%)	1168576 (10.3%)
H	1206446 (11.7%)	1238869 (11.2%)	1209062 (11.1%)	1239565 (10.9%)
W	7155432 (69.4%)	7633240 (68.7%)	7432716 (68.2%)	7719752 (67.8%)
Missing	455068 (4.4%)	667614 (6.0%)	715599 (6.6%)	846612 (7.4%)
Gender				
F	5935902 (57.6%)	6442685 (58.0%)	6318396 (58.0%)	6569240 (57.7%)
M	4375909 (42.4%)	4665997 (42.0%)	4574480 (42.0%)	4814136 (42.3%)
U	603 (0.0%)	603 (0.0%)	542 (0.0%)	520 (0.0%)
State				
AK	2912 (0.0%)	3182 (0.0%)	3167 (0.0%)	3074 (0.0%)
AL	183063 (1.8%)	198293 (1.8%)	203410 (1.9%)	209838 (1.8%)
AR	100217 (1.0%)	107526 (1.0%)	108487 (1.0%)	112436 (1.0%)
AZ	390937 (3.8%)	399635 (3.6%)	381160 (3.5%)	399635 (3.5%)
CA	932307 (9.0%)	961120 (8.7%)	932996 (8.6%)	951453 (8.4%)
CO	283980 (2.8%)	296141 (2.7%)	289847 (2.7%)	303244 (2.7%)
CT	104650 (1.0%)	167901 (1.5%)	166910 (1.5%)	178167 (1.6%)
DC	27794 (0.3%)	30021 (0.3%)	29276 (0.3%)	30828 (0.3%)
DE	11521 (0.1%)	13038 (0.1%)	12822 (0.1%)	13251 (0.1%)
FL	1026481 (10.0%)	1072711 (9.7%)	1049371 (9.6%)	1101764 (9.7%)
GA	549203 (5.3%)	569272 (5.1%)	577191 (5.3%)	595834 (5.2%)
HI	19098 (0.2%)	20489 (0.2%)	20163 (0.2%)	20621 (0.2%)
IA	112650 (1.1%)	119988 (1.1%)	118973 (1.1%)	126277 (1.1%)
ID	36066 (0.3%)	42327 (0.4%)	42590 (0.4%)	45142 (0.4%)
IL	377022 (3.7%)	425701 (3.8%)	414798 (3.8%)	425030 (3.7%)
IN	210391 (2.0%)	249217 (2.2%)	248265 (2.3%)	256652 (2.3%)
KS	62612 (0.6%)	65880 (0.6%)	64980 (0.6%)	68513 (0.6%)
KY	108321 (1.1%)	117637 (1.1%)	118639 (1.1%)	127401 (1.1%)
LA	104481 (1.0%)	108842 (1.0%)	107672 (1.0%)	113784 (1.0%)
MA	121256 (1.2%)	140606 (1.3%)	136605 (1.3%)	144938 (1.3%)
MD	178532 (1.7%)	186410 (1.7%)	176826 (1.6%)	183707 (1.6%)
ME	23717 (0.2%)	30212 (0.3%)	30226 (0.3%)	30938 (0.3%)
MI	83192 (0.8%)	89916 (0.8%)	87974 (0.8%)	91912 (0.8%)
MN	245697 (2.4%)	271174 (2.4%)	262819 (2.4%)	279409 (2.5%)
MO	290520 (2.8%)	311495 (2.8%)	309192 (2.8%)	317970 (2.8%)
MS	48462 (0.5%)	48619 (0.4%)	48150 (0.4%)	50874 (0.4%)
MT	8715 (0.1%)	9595 (0.1%)	9151 (0.1%)	9309 (0.1%)
NC	523052 (5.1%)	574876 (5.2%)	561898 (5.2%)	580700 (5.1%)
ND	30424 (0.3%)	33419 (0.3%)	32196 (0.3%)	33311 (0.3%)
NE	86994 (0.8%)	91973 (0.8%)	91177 (0.8%)	96790 (0.9%)
NH	26810 (0.3%)	33234 (0.3%)	33580 (0.3%)	34278 (0.3%)
NJ	232597 (2.3%)	251431 (2.3%)	243498 (2.2%)	259155 (2.3%)
NM	38749 (0.4%)	39913 (0.4%)	39519 (0.4%)	42706 (0.4%)
NV	63623 (0.6%)	71120 (0.6%)	72050 (0.7%)	76427 (0.7%)
NY	470001 (4.6%)	522330 (4.7%)	504091 (4.6%)	531087 (4.7%)
OH	317721 (3.1%)	359660 (3.2%)	357893 (3.3%)	378267 (3.3%)
OK	111390 (1.1%)	114806 (1.0%)	112254 (1.0%)	116828 (1.0%)
OR	108338 (1.1%)	120136 (1.1%)	113981 (1.0%)	119090 (1.0%)
PA	152234 (1.5%)	172332 (1.6%)	166136 (1.5%)	178451 (1.6%)
PR	981 (0.0%)	1176 (0.0%)	1237 (0.0%)	1279 (0.0%)
RI	43232 (0.4%)	56624 (0.5%)	55581 (0.5%)	59877 (0.5%)
SC	199697 (1.9%)	211277 (1.9%)	209723 (1.9%)	219520 (1.9%)
SD	26301 (0.3%)	28419 (0.3%)	27967 (0.3%)	28599 (0.3%)
TN	186082 (1.8%)	200724 (1.8%)	200614 (1.8%)	208636 (1.8%)
TX	1207055 (11.7%)	1257266 (11.3%)	1231607 (11.3%)	1301834 (11.4%)
UN	20851 (0.2%)	22200 (0.2%)	21605 (0.2%)	21968 (0.2%)
UT	125630 (1.2%)	128792 (1.2%)	126116 (1.2%)	131827 (1.2%)
VA	192904 (1.9%)	209861 (1.9%)	204190 (1.9%)	216932 (1.9%)
VT	9992 (0.1%)	11830 (0.1%)	11867 (0.1%)	11802 (0.1%)
WA	174591 (1.7%)	190455 (1.7%)	184519 (1.7%)	191872 (1.7%)
WI	291929 (2.8%)	317850 (2.9%)	308465 (2.8%)	319617 (2.8%)
WV	17430 (0.2%)	20340 (0.2%)	20722 (0.2%)	21614 (0.2%)
WY	10009 (0.1%)	10293 (0.1%)	9272 (0.1%)	9428 (0.1%)
CPT Code				
99201	24891 (0.2%)	23221 (0.2%)	23410 (0.2%)	28956 (0.3%)
99202	180522 (1.8%)	189361 (1.7%)	194751 (1.8%)	189277 (1.7%)
99203	569519 (5.5%)	618103 (5.6%)	623445 (5.7%)	614417 (5.4%)
99204	371629 (3.6%)	414247 (3.7%)	416095 (3.8%)	413713 (3.6%)
99205	77389 (0.8%)	86059 (0.8%)	86317 (0.8%)	85101 (0.7%)
99211	104659 (1.0%)	112917 (1.0%)	110183 (1.0%)	109705 (1.0%)
99212	394455 (3.8%)	449382 (4.0%)	441384 (4.1%)	443346 (3.9%)
99213	4261789 (41.3%)	4506593 (40.6%)	4369077 (40.1%)	4628830 (40.7%)
99214	4032692 (39.1%)	4385821 (39.5%)	4311215 (39.6%)	4548783 (40.0%)
99215	294869 (2.9%)	323581 (2.9%)	317541 (2.9%)	321768 (2.8%)

Table A6: Patient-Level Summary Statistics by Quarter, 2019

	2019q1	2019q2	2019q3	2019q4
	(N=10834139)	(N=11599315)	(N=11454335)	(N=11722721)
Telehealth				
Mean (SD)	0.000437 (0.0194)	0.000514 (0.0211)	0.000618 (0.0230)	0.000669 (0.0240)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
COVID				
Mean (SD)	0 (0)	0 (0)	0 (0)	0 (0)
Median [Min, Max]	0 [0, 0]	0 [0, 0]	0 [0, 0]	0 [0, 0]
CCI				
Mean (SD)	1.56 (2.16)	1.56 (2.15)	1.61 (2.18)	1.59 (2.18)
Median [Min, Max]	1.00 [0, 21.0]	1.00 [0, 22.0]	1.00 [0, 22.0]	1.00 [0, 22.0]
Visit Count				
Mean (SD)	1.47 (0.873)	1.48 (0.886)	1.48 (0.891)	1.46 (0.871)
Median [Min, Max]	1.00 [1.00, 84.0]	1.00 [1.00, 58.0]	1.00 [1.00, 51.0]	1.00 [1.00, 43.0]
Age				
Mean (SD)	56.9 (23.0)	57.8 (22.3)	57.9 (22.1)	56.6 (22.9)
Median [Min, Max]	64.0 [0, 90.0]	65.0 [0, 90.0]	65.0 [0, 90.0]	64.0 [0, 90.0]
Race				
A	379280 (3.5%)	393064 (3.4%)	388925 (3.4%)	398439 (3.4%)
B	1147619 (10.6%)	1215656 (10.5%)	1209043 (10.6%)	1215401 (10.4%)
H	1190791 (11.0%)	1234021 (10.6%)	1231310 (10.7%)	1242426 (10.6%)
W	7300387 (67.4%)	7844661 (67.6%)	7743651 (67.6%)	7873165 (67.2%)
Missing	816062 (7.5%)	911913 (7.9%)	881406 (7.7%)	993290 (8.5%)
Gender				
F	6250041 (57.7%)	6726083 (58.0%)	6644534 (58.0%)	6769429 (57.7%)
M	4583704 (42.3%)	4872798 (42.0%)	4809383 (42.0%)	4952872 (42.3%)
U	394 (0.0%)	434 (0.0%)	418 (0.0%)	420 (0.0%)
State				
AK	2866 (0.0%)	3132 (0.0%)	3073 (0.0%)	2946 (0.0%)
AL	213750 (2.0%)	227384 (2.0%)	232026 (2.0%)	233452 (2.0%)
AR	110209 (1.0%)	119863 (1.0%)	121312 (1.1%)	123979 (1.1%)
AZ	389768 (3.6%)	419397 (3.6%)	406419 (3.5%)	405171 (3.5%)
CA	905860 (8.4%)	895131 (7.7%)	891723 (7.8%)	894921 (7.6%)
CO	293098 (2.7%)	310752 (2.7%)	302486 (2.6%)	279791 (2.4%)
CT	168073 (1.6%)	199116 (1.7%)	198202 (1.7%)	202885 (1.7%)
DC	30319 (0.3%)	32903 (0.3%)	33052 (0.3%)	34799 (0.3%)
DE	12775 (0.1%)	13798 (0.1%)	13593 (0.1%)	13926 (0.1%)
FL	1094643 (10.1%)	1153973 (9.9%)	1121723 (9.8%)	1168643 (10.0%)
GA	586054 (5.4%)	595363 (5.1%)	594003 (5.2%)	598801 (5.1%)
HI	19511 (0.2%)	20669 (0.2%)	20629 (0.2%)	20448 (0.2%)
IA	114070 (1.1%)	142473 (1.2%)	140057 (1.2%)	148143 (1.3%)
ID	43163 (0.4%)	47861 (0.4%)	47567 (0.4%)	49013 (0.4%)
IL	387709 (3.6%)	438655 (3.8%)	431965 (3.8%)	448104 (3.8%)
IN	236750 (2.2%)	262566 (2.3%)	261096 (2.3%)	266419 (2.3%)
KS	66117 (0.6%)	71892 (0.6%)	70846 (0.6%)	73867 (0.6%)
KY	124716 (1.2%)	131291 (1.1%)	130369 (1.1%)	134180 (1.1%)
LA	108141 (1.0%)	113890 (1.0%)	115337 (1.0%)	120446 (1.0%)
MA	137188 (1.3%)	152014 (1.3%)	148114 (1.3%)	150867 (1.3%)
MD	178781 (1.7%)	186510 (1.6%)	179153 (1.6%)	186491 (1.6%)
ME	28617 (0.3%)	35431 (0.3%)	35316 (0.3%)	34152 (0.3%)
MI	81133 (0.7%)	89323 (0.8%)	85985 (0.8%)	90897 (0.8%)
MN	227361 (2.1%)	262525 (2.3%)	261176 (2.3%)	275804 (2.4%)
MO	310311 (2.9%)	351877 (3.0%)	349172 (3.0%)	352572 (3.0%)
MS	50701 (0.5%)	49614 (0.4%)	49378 (0.4%)	50343 (0.4%)
MT	8708 (0.1%)	9419 (0.1%)	9130 (0.1%)	9057 (0.1%)
NC	587533 (5.4%)	606933 (5.2%)	603110 (5.3%)	613540 (5.2%)
ND	29909 (0.3%)	34785 (0.3%)	34919 (0.3%)	36600 (0.3%)
NE	90200 (0.8%)	97862 (0.8%)	97218 (0.8%)	104025 (0.9%)
NH	31950 (0.3%)	37173 (0.3%)	37002 (0.3%)	37157 (0.3%)
NJ	241535 (2.2%)	261216 (2.3%)	254877 (2.2%)	264292 (2.3%)
NM	43641 (0.4%)	50068 (0.4%)	49174 (0.4%)	50312 (0.4%)
NV	72444 (0.7%)	80386 (0.7%)	81031 (0.7%)	83879 (0.7%)
NY	462354 (4.3%)	518720 (4.5%)	500936 (4.4%)	513553 (4.4%)
OH	343882 (3.2%)	375141 (3.2%)	368821 (3.2%)	383555 (3.3%)
OK	112942 (1.0%)	119705 (1.0%)	118380 (1.0%)	111517 (1.0%)
OR	116432 (1.1%)	137969 (1.2%)	134364 (1.2%)	128388 (1.1%)
PA	168289 (1.6%)	191098 (1.6%)	185846 (1.6%)	191168 (1.6%)
PR	1362 (0.0%)	1474 (0.0%)	1253 (0.0%)	1327 (0.0%)
RI	58533 (0.5%)	62477 (0.5%)	60593 (0.5%)	62091 (0.5%)
SC	203070 (1.9%)	210568 (1.8%)	206405 (1.8%)	211908 (1.8%)
SD	24346 (0.2%)	28526 (0.2%)	28128 (0.2%)	28189 (0.2%)
TN	203452 (1.9%)	215968 (1.9%)	216960 (1.9%)	223389 (1.9%)
TX	1247612 (11.5%)	1275174 (11.0%)	1281488 (11.2%)	1354170 (11.6%)
UN	20878 (0.2%)	21935 (0.2%)	20810 (0.2%)	17971 (0.2%)
UT	125341 (1.2%)	129573 (1.1%)	128513 (1.1%)	132987 (1.1%)
VA	212070 (2.0%)	228216 (2.0%)	223500 (2.0%)	232663 (2.0%)
VT	10917 (0.1%)	12772 (0.1%)	12969 (0.1%)	12888 (0.1%)
WA	181592 (1.7%)	199600 (1.7%)	195497 (1.7%)	182930 (1.6%)
WI	282595 (2.6%)	330090 (2.8%)	324663 (2.8%)	337817 (2.9%)
WV	21723 (0.2%)	25364 (0.2%)	25800 (0.2%)	27108 (0.2%)
WY	9145 (0.1%)	9700 (0.1%)	9176 (0.1%)	9180 (0.1%)
CPT Code				
99201	36789 (0.3%)	34408 (0.3%)	34160 (0.3%)	46300 (0.4%)
99202	175944 (1.6%)	187740 (1.6%)	192961 (1.7%)	181830 (1.6%)
99203	603158 (5.6%)	656772 (5.7%)	681133 (5.9%)	661881 (5.6%)
99204	410975 (3.8%)	452675 (3.9%)	474704 (4.1%)	475233 (4.1%)
99205	83468 (0.8%)	93000 (0.8%)	98208 (0.9%)	97327 (0.8%)
99211	96920 (0.9%)	103184 (0.9%)	104677 (0.9%)	104153 (0.9%)
99212	402098 (3.7%)	442099 (3.8%)	436396 (3.8%)	428561 (3.7%)
99213	4317672 (39.9%)	4577825 (39.5%)	4449475 (38.8%)	4616773 (39.4%)
99214	4392547 (40.5%)	4715108 (40.6%)	4648594 (40.6%)	4777501 (40.8%)
99215	314568 (2.9%)	336504 (2.9%)	334027 (2.9%)	333162 (2.8%)

Table A7: Patient-Level Summary Statistics by Quarter, 2020

	2020q1	2020q2	2020q3	2020q4
	(N=10333958)	(N=8858654)	(N=10899208)	(N=11140968)
Telehealth				
Mean (SD)	0.0173 (0.121)	0.250 (0.411)	0.124 (0.308)	0.121 (0.304)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
COVID				
Mean (SD)	0.00292 (0.0503)	0.0309 (0.163)	0.0423 (0.190)	0.0776 (0.255)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
CCI				
Mean (SD)	1.63 (2.22)	1.68 (2.24)	1.63 (2.19)	1.61 (2.19)
Median [Min, Max]	1.00 [0, 22.0]	1.00 [0, 22.0]	1.00 [0, 23.0]	1.00 [0, 22.0]
Visit Count				
Mean (SD)	1.47 (0.873)	1.46 (0.889)	1.49 (0.911)	1.48 (0.904)
Median [Min, Max]	1.00 [1.00, 59.0]	1.00 [1.00, 48.0]	1.00 [1.00, 55.0]	1.00 [1.00, 59.0]
Age				
Mean (SD)	57.3 (22.8)	59.0 (20.8)	59.0 (21.1)	58.0 (21.4)
Median [Min, Max]	64.0 [0, 90.0]	65.0 [0, 90.0]	66.0 [0, 90.0]	65.0 [0, 90.0]
Race				
A	334545 (3.2%)	253551 (2.9%)	340341 (3.1%)	360640 (3.2%)
B	1088168 (10.5%)	982698 (11.1%)	1171609 (10.7%)	1180189 (10.6%)
H	1131424 (10.9%)	940269 (10.6%)	1139988 (10.5%)	1176102 (10.6%)
W	6877176 (66.5%)	5977292 (67.5%)	7352268 (67.5%)	7447201 (66.8%)
Missing	902645 (8.7%)	704844 (8.0%)	895002 (8.2%)	976836 (8.8%)
Gender				
F	5954360 (57.6%)	5125766 (57.9%)	6339312 (58.2%)	6456847 (58.0%)
M	4379249 (42.4%)	3732554 (42.1%)	4559452 (41.8%)	4683654 (42.0%)
U	349 (0.0%)	334 (0.0%)	444 (0.0%)	467 (0.0%)
State				
AK	2384 (0.0%)	1996 (0.0%)	2325 (0.0%)	2264 (0.0%)
AL	133688 (1.3%)	150009 (1.7%)	175229 (1.6%)	177266 (1.6%)
AR	114656 (1.1%)	107459 (1.2%)	127744 (1.2%)	131289 (1.2%)
AZ	391460 (3.8%)	342739 (3.9%)	391152 (3.6%)	417531 (3.7%)
CA	773627 (7.5%)	587478 (6.6%)	763459 (7.0%)	788593 (7.1%)
CO	287133 (2.8%)	246976 (2.8%)	281710 (2.6%)	285144 (2.6%)
CT	181234 (1.8%)	152758 (1.7%)	204176 (1.9%)	204030 (1.8%)
DC	31538 (0.3%)	25142 (0.3%)	30444 (0.3%)	33165 (0.3%)
DE	11731 (0.1%)	9533 (0.1%)	11867 (0.1%)	11996 (0.1%)
FL	1059475 (10.3%)	906646 (10.2%)	1042671 (9.6%)	1065913 (9.6%)
GA	533668 (5.2%)	469324 (5.3%)	559761 (5.1%)	564299 (5.1%)
HI	18253 (0.2%)	15586 (0.2%)	19687 (0.2%)	20143 (0.2%)
IA	115154 (1.1%)	94763 (1.1%)	121000 (1.1%)	122749 (1.1%)
ID	43966 (0.4%)	40232 (0.5%)	49577 (0.5%)	50224 (0.5%)
IL	382111 (3.7%)	317713 (3.6%)	417709 (3.8%)	423478 (3.8%)
IN	227043 (2.2%)	198724 (2.2%)	265526 (2.4%)	260752 (2.3%)
KS	63839 (0.6%)	56233 (0.6%)	68687 (0.6%)	69225 (0.6%)
KY	115915 (1.1%)	93342 (1.1%)	121155 (1.1%)	120041 (1.1%)
LA	98112 (0.9%)	79529 (0.9%)	93627 (0.9%)	96852 (0.9%)
MA	127233 (1.2%)	110043 (1.2%)	138543 (1.3%)	142147 (1.3%)
MD	167871 (1.6%)	127907 (1.4%)	160237 (1.5%)	166826 (1.5%)
ME	29044 (0.3%)	24234 (0.3%)	32920 (0.3%)	32629 (0.3%)
MI	74640 (0.7%)	58460 (0.7%)	75887 (0.7%)	75997 (0.7%)
MN	223013 (2.2%)	194357 (2.2%)	250401 (2.3%)	258533 (2.3%)
MO	318309 (3.1%)	272273 (3.1%)	337895 (3.1%)	330442 (3.0%)
MS	45707 (0.4%)	39639 (0.4%)	48198 (0.4%)	49944 (0.4%)
MT	7886 (0.1%)	6764 (0.1%)	8495 (0.1%)	8524 (0.1%)
NC	575706 (5.6%)	506662 (5.7%)	614579 (5.6%)	617218 (5.5%)
ND	31869 (0.3%)	28318 (0.3%)	34692 (0.3%)	34686 (0.3%)
NE	81540 (0.8%)	69318 (0.8%)	83332 (0.8%)	82124 (0.7%)
NH	30174 (0.3%)	26452 (0.3%)	36176 (0.3%)	36213 (0.3%)
NJ	229594 (2.2%)	184174 (2.1%)	242572 (2.2%)	253044 (2.3%)
NM	46223 (0.4%)	38810 (0.4%)	48276 (0.4%)	47498 (0.4%)
NV	74689 (0.7%)	64705 (0.7%)	85455 (0.8%)	90032 (0.8%)
NY	428298 (4.1%)	360182 (4.1%)	486405 (4.5%)	526850 (4.7%)
OH	326599 (3.2%)	286785 (3.2%)	364449 (3.3%)	368116 (3.3%)
OK	109435 (1.1%)	102706 (1.2%)	122908 (1.1%)	121219 (1.1%)
OR	123114 (1.2%)	113090 (1.3%)	140984 (1.3%)	146486 (1.3%)
PA	157286 (1.5%)	132994 (1.5%)	170738 (1.6%)	169707 (1.5%)
PR	1144 (0.0%)	888 (0.0%)	1150 (0.0%)	1187 (0.0%)
RI	58697 (0.6%)	53639 (0.6%)	59898 (0.5%)	59508 (0.5%)
SC	189238 (1.8%)	172838 (2.0%)	202790 (1.9%)	203443 (1.8%)
SD	24074 (0.2%)	21611 (0.2%)	29120 (0.3%)	28345 (0.3%)
TN	199741 (1.9%)	182224 (2.1%)	218105 (2.0%)	222300 (2.0%)
TX	1228321 (11.9%)	1074544 (12.1%)	1236155 (11.3%)	1294373 (11.6%)
UN	18444 (0.2%)	10482 (0.1%)	13015 (0.1%)	13309 (0.1%)
UT	122252 (1.2%)	110401 (1.2%)	130217 (1.2%)	139578 (1.3%)
VA	204240 (2.0%)	168911 (1.9%)	208527 (1.9%)	213044 (1.9%)
VT	10774 (0.1%)	10228 (0.1%)	13703 (0.1%)	13059 (0.1%)
WA	164544 (1.6%)	140212 (1.6%)	182082 (1.7%)	183966 (1.7%)
WI	286775 (2.8%)	240392 (2.7%)	338156 (3.1%)	330446 (3.0%)
WV	24585 (0.2%)	21909 (0.2%)	27454 (0.3%)	27097 (0.2%)
WY	7912 (0.1%)	6320 (0.1%)	8188 (0.1%)	8124 (0.1%)
CPT Code				
99201	54197 (0.5%)	60068 (0.7%)	61712 (0.6%)	64865 (0.6%)
99202	163214 (1.6%)	143727 (1.6%)	204628 (1.9%)	233064 (2.1%)
99203	586838 (5.7%)	419490 (4.7%)	654836 (6.0%)	683154 (6.1%)
99204	435452 (4.2%)	303914 (3.4%)	460133 (4.2%)	472570 (4.2%)
99205	89711 (0.9%)	64653 (0.7%)	92917 (0.9%)	94202 (0.8%)
99211	90866 (0.9%)	137059 (1.5%)	200522 (1.8%)	263417 (2.4%)
99212	367798 (3.6%)	420954 (4.8%)	447886 (4.1%)	470331 (4.2%)
99213	4011110 (38.8%)	3550261 (40.1%)	4091143 (37.5%)	4171266 (37.4%)
99214	4233551 (41.0%)	3514311 (39.7%)	4371896 (40.1%)	4372682 (39.2%)
99215	301221 (2.9%)	244217 (2.8%)	313535 (2.9%)	315417 (2.8%)

Table A8: Patient-Level Summary Statistics by Quarter, 2021-2022q1

	2021q1	2021q2	2021q3	2021q4	2022q1
	(N=10426346)	(N=12078543)	(N=12493289)	(N=12504852)	(N=11387594)
Telehealth					
Mean (SD)	0.105 (0.286)	0.0676 (0.233)	0.0596 (0.220)	0.0600 (0.221)	0.0705 (0.238)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
COVID					
Mean (SD)	0.0671 (0.238)	0.0354 (0.175)	0.0602 (0.226)	0.0656 (0.235)	0.0649 (0.234)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
CCI					
Mean (SD)	1.63 (2.20)	1.59 (2.16)	1.64 (2.20)	1.65 (2.21)	1.72 (2.24)
Median [Min, Max]	1.00 [0, 23.0]	1.00 [0, 23.0]	1.00 [0, 23.0]	1.00 [0, 23.0]	1.00 [0, 23.0]
Visit Count					
Mean (SD)	1.50 (0.929)	1.50 (0.916)	1.49 (0.891)	1.46 (0.859)	1.47 (0.865)
Median [Min, Max]	1.00 [1.00, 47.0]	1.00 [1.00, 53.0]	1.00 [1.00, 52.0]	1.00 [1.00, 33.0]	1.00 [1.00, 59.0]
Age					
Mean (SD)	58.9 (21.4)	59.5 (21.5)	58.9 (21.8)	58.3 (22.1)	59.9 (21.7)
Median [Min, Max]	66.0 [0, 90.0]	66.0 [0, 90.0]	66.0 [0, 90.0]	66.0 [0, 90.0]	67.0 [0, 90.0]
Race					
A	328730 (3.2%)	375091 (3.1%)	395958 (3.2%)	398091 (3.2%)	345259 (3.0%)
B	1097906 (10.5%)	1252165 (10.4%)	1275336 (10.2%)	1247004 (10.0%)	1127328 (9.9%)
H	1106514 (10.6%)	1237304 (10.2%)	1266468 (10.1%)	1242116 (9.9%)	1124976 (9.9%)
W	6950431 (66.7%)	8000840 (66.2%)	8218183 (65.8%)	8172025 (65.4%)	7478639 (65.7%)
Missing	942765 (9.0%)	1213143 (10.0%)	1337344 (10.7%)	1445616 (11.6%)	1311392 (11.5%)
Gender					
F	6008077 (57.6%)	7015948 (58.1%)	7228602 (57.9%)	7215017 (57.7%)	6563293 (57.6%)
M	4417808 (42.4%)	5061995 (41.9%)	5264015 (42.1%)	5288989 (42.3%)	4823476 (42.4%)
U	461 (0.0%)	600 (0.0%)	672 (0.0%)	846 (0.0%)	825 (0.0%)
State					
AK	1995 (0.0%)	2495 (0.0%)	2520 (0.0%)	2224 (0.0%)	2056 (0.0%)
AL	175438 (1.7%)	199255 (1.6%)	208857 (1.7%)	206182 (1.6%)	202569 (1.8%)
AR	119597 (1.1%)	144026 (1.2%)	150090 (1.2%)	146951 (1.2%)	135256 (1.2%)
AZ	415590 (4.0%)	447341 (3.7%)	441582 (3.5%)	420707 (3.4%)	383285 (3.4%)
CA	727886 (7.0%)	790614 (6.5%)	823455 (6.6%)	801792 (6.4%)	728734 (6.4%)
CO	282927 (2.7%)	319444 (2.6%)	327680 (2.6%)	283757 (2.3%)	229934 (2.0%)
CT	198620 (1.9%)	237078 (2.0%)	246270 (2.0%)	253336 (2.0%)	231506 (2.0%)
DC	32742 (0.3%)	34866 (0.3%)	33915 (0.3%)	33290 (0.3%)	20723 (0.2%)
DE	11693 (0.1%)	19338 (0.2%)	20683 (0.2%)	21036 (0.2%)	19685 (0.2%)
FL	1085121 (10.4%)	1162997 (9.6%)	1151092 (9.2%)	1169091 (9.3%)	1108633 (9.7%)
GA	554956 (5.3%)	582597 (4.8%)	607388 (4.9%)	591144 (4.7%)	549207 (4.8%)
HI	20161 (0.2%)	22352 (0.2%)	22753 (0.2%)	21848 (0.2%)	18801 (0.2%)
IA	113494 (1.1%)	134551 (1.1%)	141166 (1.1%)	143479 (1.1%)	128262 (1.1%)
ID	49493 (0.5%)	59420 (0.5%)	61699 (0.5%)	60297 (0.5%)	56704 (0.5%)
IL	401246 (3.8%)	474580 (3.9%)	495179 (4.0%)	500949 (4.0%)	449475 (3.9%)
IN	253636 (2.4%)	307446 (2.5%)	319747 (2.6%)	312732 (2.5%)	280845 (2.5%)
KS	64661 (0.6%)	90552 (0.7%)	95976 (0.8%)	97366 (0.8%)	84275 (0.7%)
KY	111923 (1.1%)	125416 (1.0%)	133456 (1.1%)	135210 (1.1%)	122723 (1.1%)
LA	91669 (0.9%)	103491 (0.9%)	105623 (0.8%)	109543 (0.9%)	92990 (0.8%)
MA	138062 (1.3%)	167726 (1.4%)	173438 (1.4%)	180045 (1.4%)	162831 (1.4%)
MD	162529 (1.6%)	178158 (1.5%)	184515 (1.5%)	186926 (1.5%)	172122 (1.5%)
ME	30775 (0.3%)	38223 (0.3%)	40239 (0.3%)	38621 (0.3%)	33580 (0.3%)
MI	72381 (0.7%)	85688 (0.7%)	89473 (0.7%)	90177 (0.7%)	76321 (0.7%)
MN	221753 (2.1%)	263599 (2.2%)	273794 (2.2%)	286492 (2.3%)	253685 (2.2%)
MO	320661 (3.1%)	386297 (3.2%)	400945 (3.2%)	397292 (3.2%)	358417 (3.1%)
MS	47377 (0.5%)	58421 (0.5%)	64268 (0.5%)	61947 (0.5%)	56148 (0.5%)
MT	8097 (0.1%)	9652 (0.1%)	10254 (0.1%)	9557 (0.1%)	8421 (0.1%)
NC	439974 (4.2%)	502140 (4.2%)	526486 (4.2%)	518181 (4.1%)	480360 (4.2%)
ND	33472 (0.3%)	40275 (0.3%)	42482 (0.3%)	43872 (0.4%)	36906 (0.3%)
NE	73810 (0.7%)	86902 (0.7%)	91644 (0.7%)	93877 (0.8%)	80879 (0.7%)
NH	34761 (0.3%)	42951 (0.4%)	45568 (0.4%)	45956 (0.4%)	41246 (0.4%)
NJ	233841 (2.2%)	271153 (2.2%)	275294 (2.2%)	287807 (2.3%)	250329 (2.2%)
NM	48743 (0.5%)	64188 (0.5%)	66674 (0.5%)	64905 (0.5%)	60177 (0.5%)
NV	88078 (0.8%)	108742 (0.9%)	114714 (0.9%)	113156 (0.9%)	101763 (0.9%)
NY	463312 (4.4%)	524960 (4.3%)	524094 (4.2%)	543889 (4.3%)	464459 (4.1%)
OH	348848 (3.3%)	404140 (3.3%)	421041 (3.4%)	420899 (3.4%)	371223 (3.3%)
OK	111819 (1.1%)	147381 (1.2%)	154073 (1.2%)	134668 (1.1%)	132576 (1.2%)
OR	141070 (1.4%)	161679 (1.3%)	165263 (1.3%)	135663 (1.1%)	114606 (1.0%)
PA	161086 (1.5%)	200786 (1.7%)	208308 (1.7%)	211082 (1.7%)	186876 (1.6%)
PR	1083 (0.0%)	1250 (0.0%)	1311 (0.0%)	1314 (0.0%)	1108 (0.0%)
RI	50696 (0.5%)	59159 (0.5%)	59723 (0.5%)	60335 (0.5%)	57338 (0.5%)
SC	197736 (1.9%)	222129 (1.8%)	230921 (1.8%)	227421 (1.8%)	208325 (1.8%)
SD	27959 (0.3%)	36605 (0.3%)	39148 (0.3%)	39189 (0.3%)	36063 (0.3%)
TN	213187 (2.0%)	243318 (2.0%)	260344 (2.1%)	257560 (2.1%)	236749 (2.1%)
TX	1153013 (11.1%)	1489665 (12.3%)	1570578 (12.6%)	1537436 (12.3%)	1393986 (12.2%)
UN	11607 (0.1%)	15211 (0.1%)	19782 (0.2%)	159036 (1.3%)	222685 (2.0%)
UT	128966 (1.2%)	140815 (1.2%)	146142 (1.2%)	146772 (1.2%)	137338 (1.2%)
VA	203406 (2.0%)	236029 (2.0%)	246451 (2.0%)	248003 (2.0%)	222756 (2.0%)
VT	12728 (0.1%)	15704 (0.1%)	16372 (0.1%)	15821 (0.1%)	14146 (0.1%)
WA	175974 (1.7%)	206067 (1.7%)	210885 (1.7%)	191247 (1.5%)	160838 (1.4%)
WI	322616 (3.1%)	368974 (3.1%)	383917 (3.1%)	380425 (3.0%)	343732 (3.0%)
WV	26754 (0.3%)	34379 (0.3%)	37384 (0.3%)	55972 (0.4%)	56258 (0.5%)
WY	7324 (0.1%)	8318 (0.1%)	8633 (0.1%)	8375 (0.1%)	7684 (0.1%)
CPT Code					
99201	163 (0.0%)	115 (0.0%)	98 (0.0%)	57 (0.0%)	34 (0.0%)
99202	206853 (2.0%)	186741 (1.5%)	197003 (1.6%)	185071 (1.5%)	152129 (1.3%)
99203	583137 (5.6%)	685152 (5.7%)	740525 (5.9%)	698302 (5.6%)	618046 (5.4%)
99204	538179 (5.2%)	670004 (5.5%)	696654 (5.6%)	681593 (5.5%)	646730 (5.7%)
99205	98057 (0.9%)	118645 (1.0%)	121573 (1.0%)	119147 (1.0%)	113936 (1.0%)
99211	198748 (1.9%)	179079 (1.5%)	253143 (2.0%)	276007 (2.2%)	226372 (2.0%)
99212	493612 (4.7%)	503682 (4.2%)	504411 (4.0%)	489851 (3.9%)	421816 (3.7%)
99213	3674722 (35.2%)	4255209 (35.2%)	4431537 (35.5%)	4466783 (35.7%)	3942130 (34.6%)
99214	4276785 (41.0%)	5060584 (41.9%)	5127543 (41.0%)	5163153 (41.3%)	4852356 (42.6%)
99215	356090 (3.4%)	419332 (3.5%)	420802 (3.4%)	424888 (3.4%)	414045 (3.6%)

B Heterogeneity by Patient and Provider

To accompany the main results presented in this paper, I partition the data by patient and provider characteristics and report telehealth usage trends and results with respect to patient and provider heterogeneity.

B.1 By Patient

First, I investigate overall trends in telehealth usage and the reduced-form results by exploiting observable patient heterogeneity in the data. There are three main dimensions of patient differences that I observe. First, using the differences in CPT® codes across both face-to-face and telehealth office/outpatient E/M services, I can differentiate those who are established patients (those who have received professional services by a given physician or health care professional or another of the same specialty and subspecialty within the same group practice) relative to those who are new patients. Additionally, I can identify if patients have a referring provider associated with a service encounter or instead if patients do not have a referral. Finally, I use data on member enrollment to capture whether a patient had either commercial non-Medicare insurance or a Medicare Advantage plan when the service visit occurred.

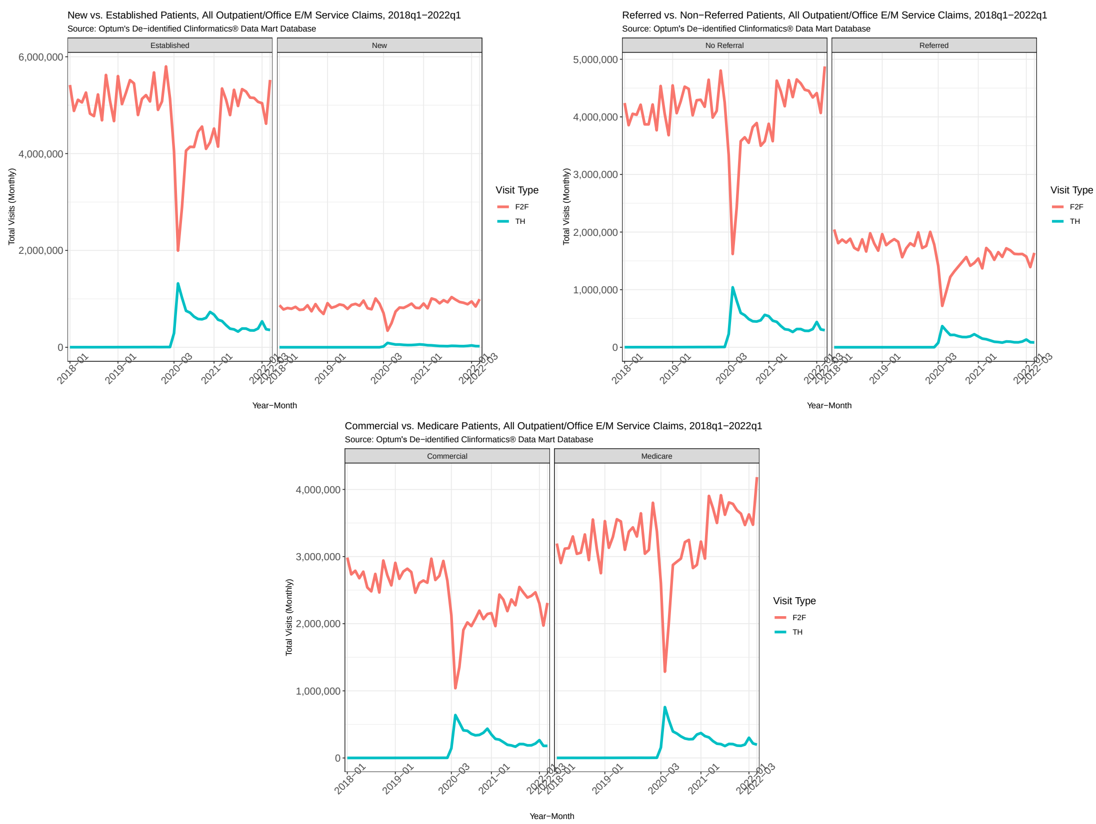


Figure B1: Telehealth vs. Face-to-Face Trends by Patient Type

Trends in telehealth and face-to-face care by patient heterogeneity are shown in Figure B1. Established patients (CPT® codes 99211-99215) make up the majority of the observed claims and dictate much of the trends shown in Figure 1. However, office/outpatient E/M service claims from new patients (CPT® codes 99201-99205) appear to have similar patterns in telehealth and face-to-face care, although at a much smaller scale. Similarly, claims from patients without a referring provider outnumber claims with a referral by roughly two-to-one, but both sets of patients experience common trends in telehealth and face-to-face care. Patients with Medicare Advantage plans contribute to a slight majority of claims in these data relative to commercially insured patients, but, again, both groups face similarities in telehealth and face-to-face usage over time.

To estimate heterogeneous impacts of telehealth usage by patient type, I partition the data by patient type and estimate the average marginal effects in each month-year cohort. Figures B2 through B5 display results by patient type, severe health outcome, and level of analysis. To show distinctions between patient type, I limit to the month-year cohorts of March 2020 and onward. Generally speaking, across encounter and patient results, the average marginal effects in each month-year cohort are larger for established patients versus new patients, non-referred versus referred, and Medicare Advantage versus commercially insured patients.

The most substantial gap in estimated impact of telehealth usage on severe health outcomes is between Medicare Advantage and commercially insured patients. There are two key takeaways from results by insurance type. First, when I am partitioning by insurance type in this context, I am essentially partitioning into younger and older cohorts. As a result, the dependency of observable health outcomes on underlying health status should be front of mind, since the thresholds for experiencing a severe health outcome are vastly different by age alone. Thus, it should be unsurprising that I find relatively small or insignificant effects on likelihood of mortality of telehealth usage for the commercially insured patients and larger, significant effects on likelihood of ER visit. Second, that the results are so stark for Medicare Advantage patients highlights how crucial it is to identify the proper role of telehealth usage in the Medicare-eligible population moving forward.

The evidence I find with referred and non-referred patients as well as established and new patients is more mixed. In many cases, confidence intervals of referred versus non-referred and established versus new patients overlap, suggesting that the impacts of telehealth usage may be more similar than different across groups. To the extent that referred patients experience lower likelihood of severe health outcomes through telehealth usage than non-referred patients, this suggests there may be improvements in outcomes by pairing synchronous telehealth usage with other forms of consultation prior to the visit. Similarly, when considering differences in established versus new patients, there may be a lesser effect on new patients because patients are better off by increasing access to care on the margin. Future work exploring how patient groups are impacted by various forms of telehealth services is vital for understanding the role of telehealth in health care going forward.

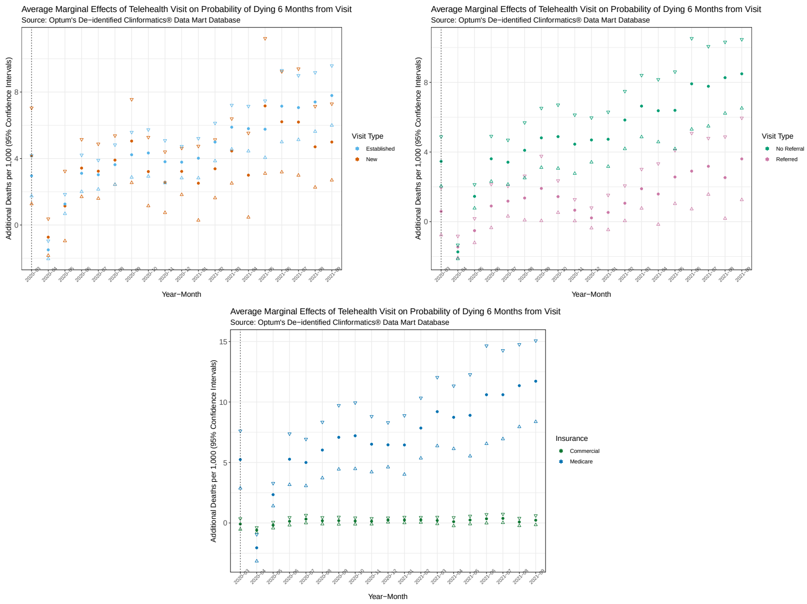


Figure B2: (Mortality) Encounter-Level Reduced-Form Estimation Results, by Patient Heterogeneity

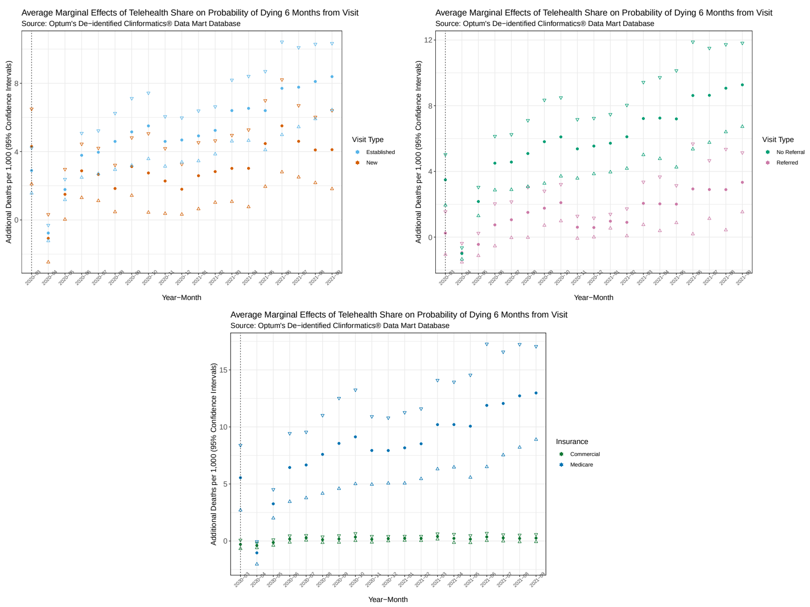


Figure B3: (Mortality) Patient-Level Reduced-Form Estimation Results, by Patient Heterogeneity

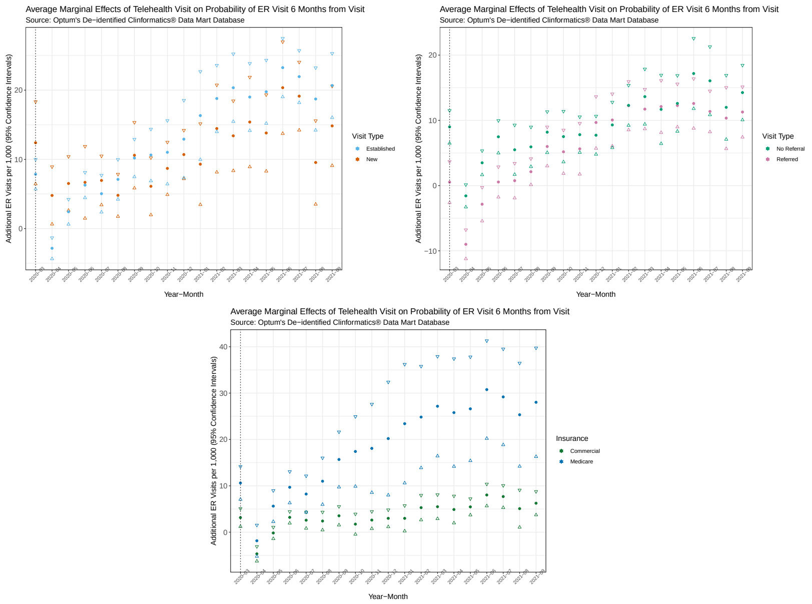


Figure B4: (ER Visit) Encounter-Level Reduced-Form Estimation Results, by Patient Heterogeneity

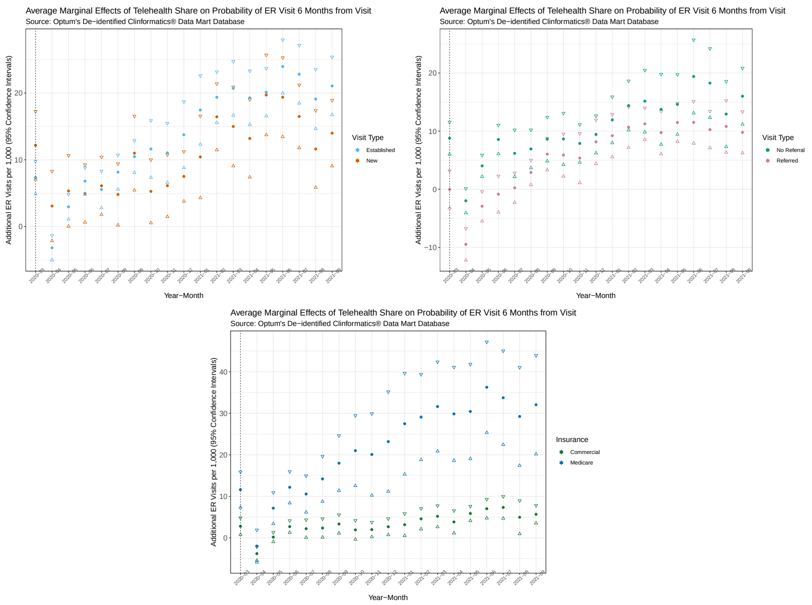


Figure B5: (ER Visit) Patient-Level Reduced-Form Estimation Results, by Patient Heterogeneity

B.2 By Provider

Next, I exploit provider heterogeneity in category of care provision to examine trends and reduced-form results comparing telehealth and face-to-face care. Here, I separate health care providers who have office/outpatient E/M service visits into three mutually exclusive groups: primary care physicians, specialty physicians, and other non-physician providers.

Figure B6 displays the evolution of face-to-face and telehealth services for each provider category from each quarter between the beginning of 2018 and beginning of 2022. Primary care and specialist visits are the majority of both face-to-face and post-March 2020 telehealth visits. Other non-physician providers, primarily consisting of nurse practitioners, experience less of a decline in face-to-face visits and less of a surge in telehealth visits at the onset of the COVID-19 pandemic. However, primary care and specialist care is always greater in number of encounters in telehealth and face-to-face categories.

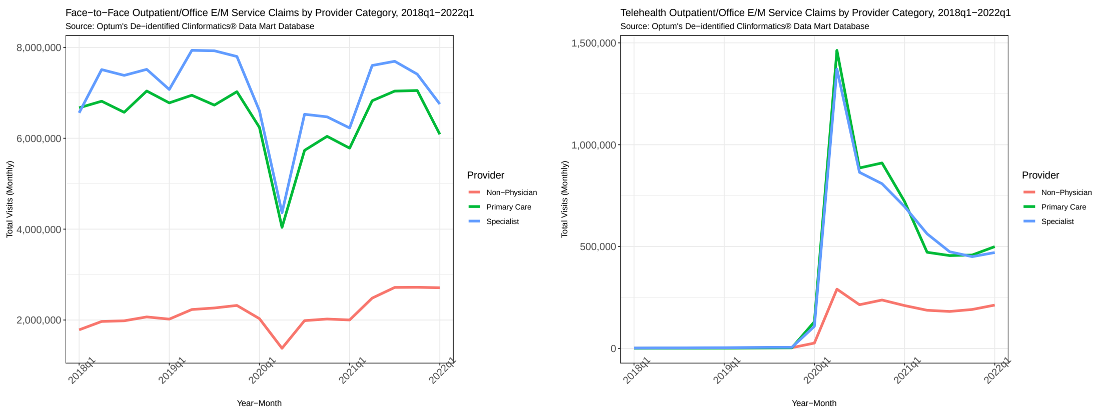


Figure B6: Telehealth vs. Face-to-Face Trends by Provider Specialty

I partition the data by provider category and obtain reduced-form results at the encounter level for likelihood of mortality and ER visit within 6 months. These results are displayed in Figures B7 through B9. Ultimately, I find that results across provider category follow the patterns and magnitudes shown in the main results. While there are some differences across provider category in magnitude, especially in consideration of April 2020, I find these results reflect the changes in patients receiving face-to-face care in the early phase of the COVID-19 pandemic. Over time, we see a consistent pattern of the impact of telehealth usage on measured health outcomes across provider category.

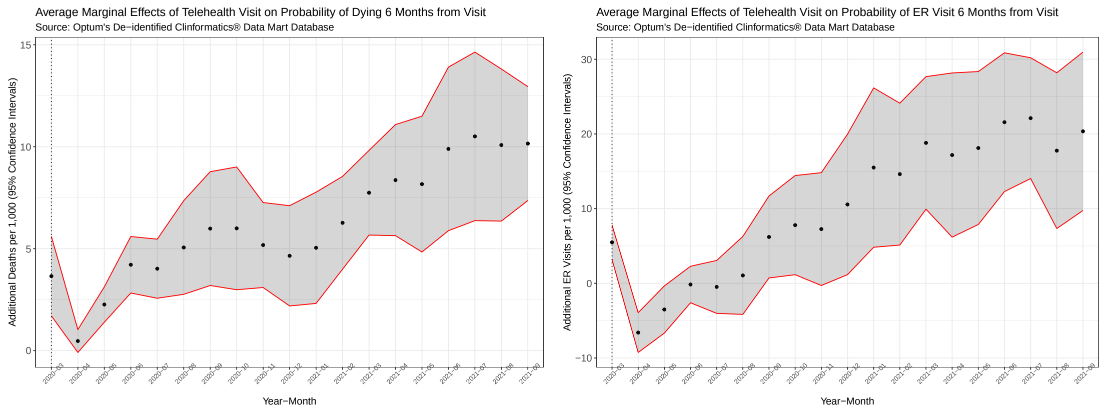


Figure B7: Encounter-Level Reduced-Form Estimation Results, Primary Care Providers

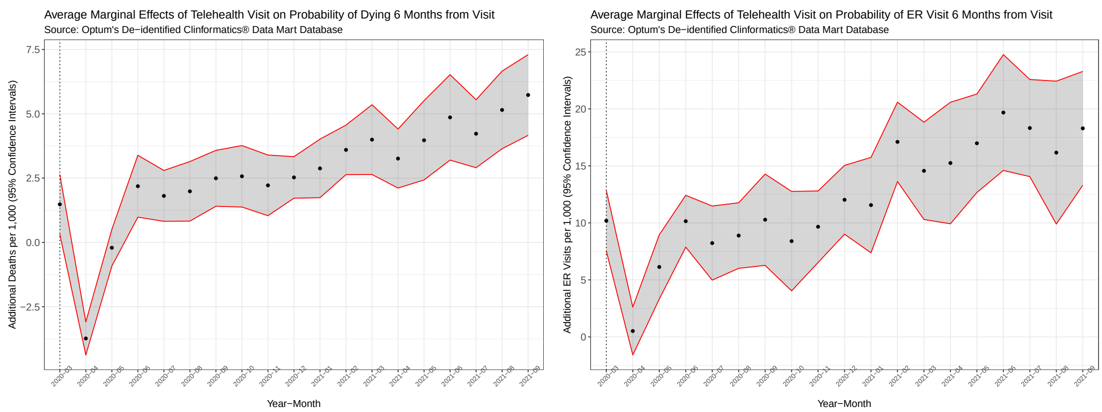


Figure B8: Encounter-Level Reduced-Form Estimation Results, Specialty Providers

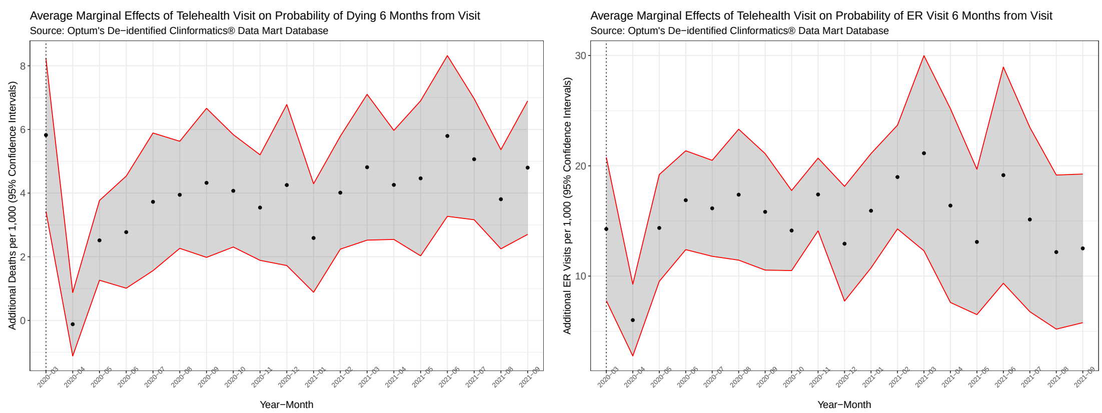


Figure B9: Encounter-Level Reduced-Form Estimation Results, Other Non-Physician Providers

C Robustness Checks

In this section of the appendix, I provide a series of additional tests to obtain the validity of the main results. First, I provide additional support regarding the alternative specifications used in the main body of the paper: inverse propensity score weighting and using provider telehealth propensity as an instrumental variable. Next, I perform a set of sensitivity analyses to strengthen the conclusions from the main results. I also take a closer look into potential sources of endogeneity and discuss how I address them. Finally, I comment on the level of clustering of standard errors that is used throughout the paper.

C.1 Propensity Score Weighting

In the reduced-form empirical framework of this paper, there may be a concern that the results from the estimation procedures reflect a insufficient level of balance in covariates across telehealth and face-to-face observations rather than the differences in outcomes across visit modality. To address this concern, I detail in Section 4.2.1 the construction of propensity scores used to reweight observations by both inverse propensity score weights and overlap weights, which are then used to create an alternative set of specifications to the main results, as presented in Section 5.1.

Figure C1 displays the propensity score distributions across telehealth and face-to-face visit modalities for each quarter. While the quarters leading up to the COVID-19 pandemic reflect distributions concentrated around zero for both modalities, the remaining quarters display propensity score distributions with much overlap across visit modality. This difference between pre- and post-March 2020 distributions reflects the sharp contrast in telehealth usage between the two periods. The explanatory power of covariates evolves over time due to telehealth usage being relatively rare in the pre-pandemic period.

Figure C2 displays absolute standardized mean differences across unweighted and weighted observations for each covariate across each quarter. The unweighted standardized mean differences are already relatively small, often near or under 0.1 in most categories. Weighted observations using either inverse propensity score weights or overlap weights improve balance such that most covariates have standardized mean differences below 0.1 and near zero. While I use this exercise to show improvement in balance using weighted observations, these plots also visualize the pre-existing balance in the unweighted observations used in the main results.

Figures C3 and C4 display the estimation results for encounter, patient, and provider levels of analysis when including IPW and OLP weights, respectively. Both weighting strategies return similar results to the unweighted results in Section 5. These figures are the full estimation results corresponding to Table 2 in Section 5.1.

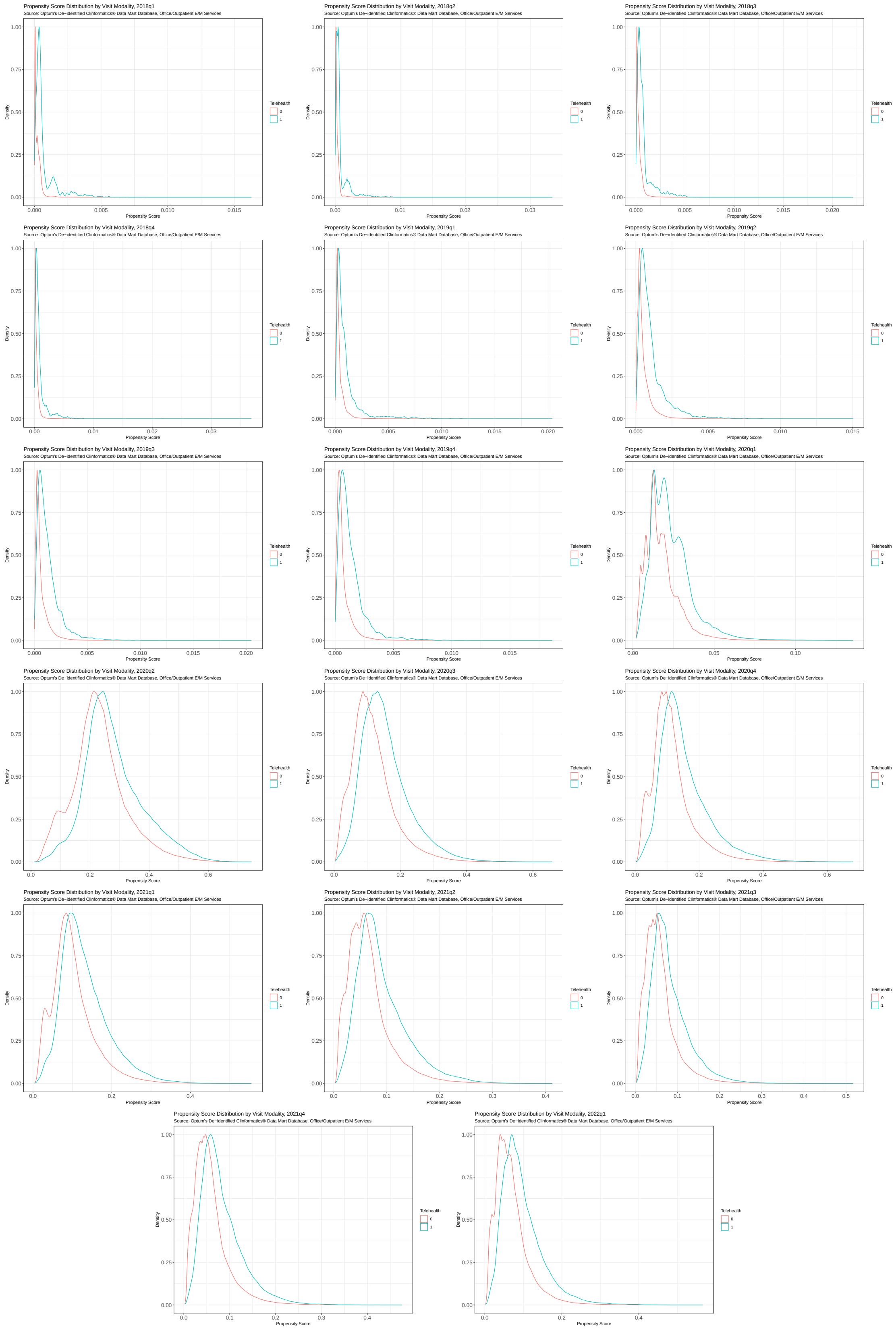


Figure C1: Propensity Score Distribution by Telehealth Usage, 2018q1 to 2022q1

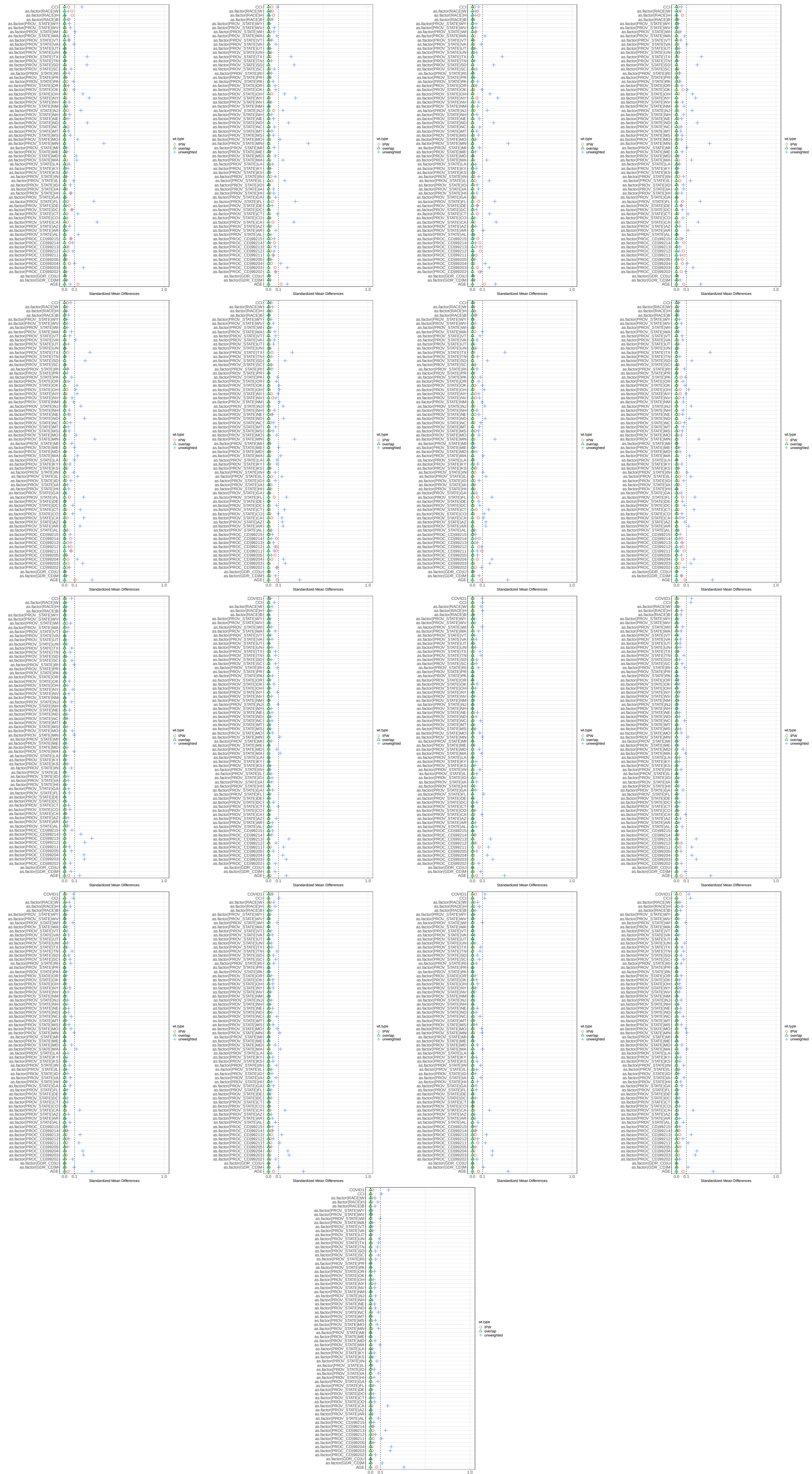


Figure C2: Balance of Covariates, 2018q1 to 2022q1

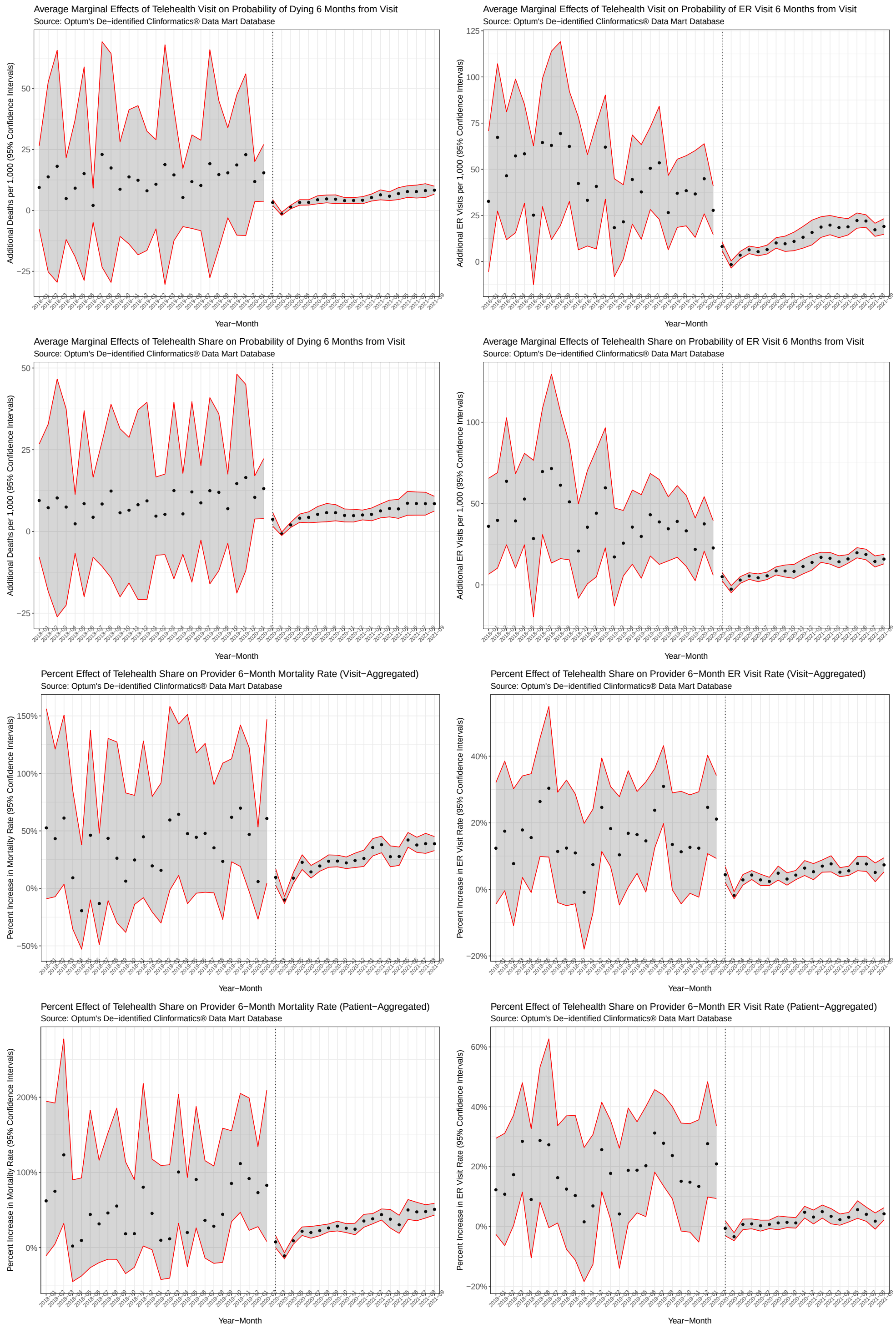


Figure C3: Reduced-Form Estimation Results with IPW

Figure C4: Reduced-Form Estimation Results with OLP

C.2 Instrumental Variable

Because of potential endogeneity in the use of telehealth at the encounter level, I construct a leave-one-out provider propensity to use telehealth measure, and I use this as an instrument as detailed in Section 4.2.2. I use a two-stage least squares (2SLS) instrumental variable approach and the results are displayed in Section 5.2.

To establish the legitimacy of moving from a nonlinear to linear model for the instrumental variables approach, I estimate the baseline model at the encounter level in Equation 12 using ordinary least squares (OLS) rather than using logistic regression. Figure C5 displays these results, which are very similar to the logistic encounter-level results in Figure 4. As a result, I proceed forward with the 2SLS estimation with confidence that the method of model estimation is not driving differences in results.

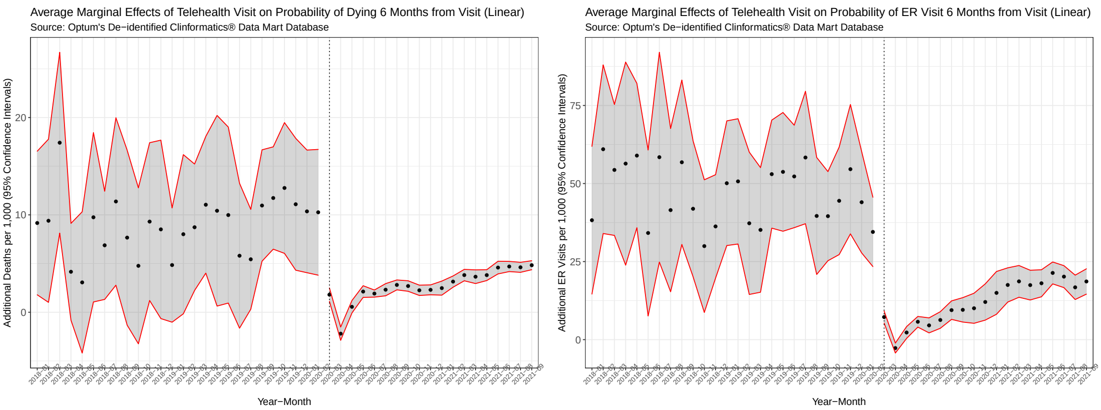


Figure C5: Encounter-Level Reduced-Form Estimation Results

For provider telehealth propensity to be a valid instrument, it must satisfy a series of restricting assumptions, as discussed in Section 4.2.2. For support, I plot the balance across encounters above or equal to and below median values of (leave-one-out) provider propensity to use telehealth for observed factors.

Figure C6 displays balance plots across each quarter in my sample. For the most part, balance is observed within an acceptable threshold (less than 0.1 SMD) across most observed factors, which is similar to the degree of underlying balance observed in telehealth use seen when constructing propensity score weights, an encouraging finding given that we are looking at balance in a flag for being above or equal to and below the median provider propensity to use telehealth. Additionally, observed levels of imbalance (SMD beyond 0.1) typically are reflected in provider state of operation and CPT® code, but these variables are also used in the construction of provider telehealth propensity alongside month cohort and provider identifier. Other patient factors, such as CCI, age, or race, may sometimes reflect imbalance, but this is not as frequent in the post-March 2020 period and may reflect more on the pre-pandemic context of telehealth use, which we interpret cautiously.

Finally, Figure C7 displays the distribution by quarter of the instrument, which reflects similar takeaways as the discussion of provider propensity to use telehealth in Section 3.

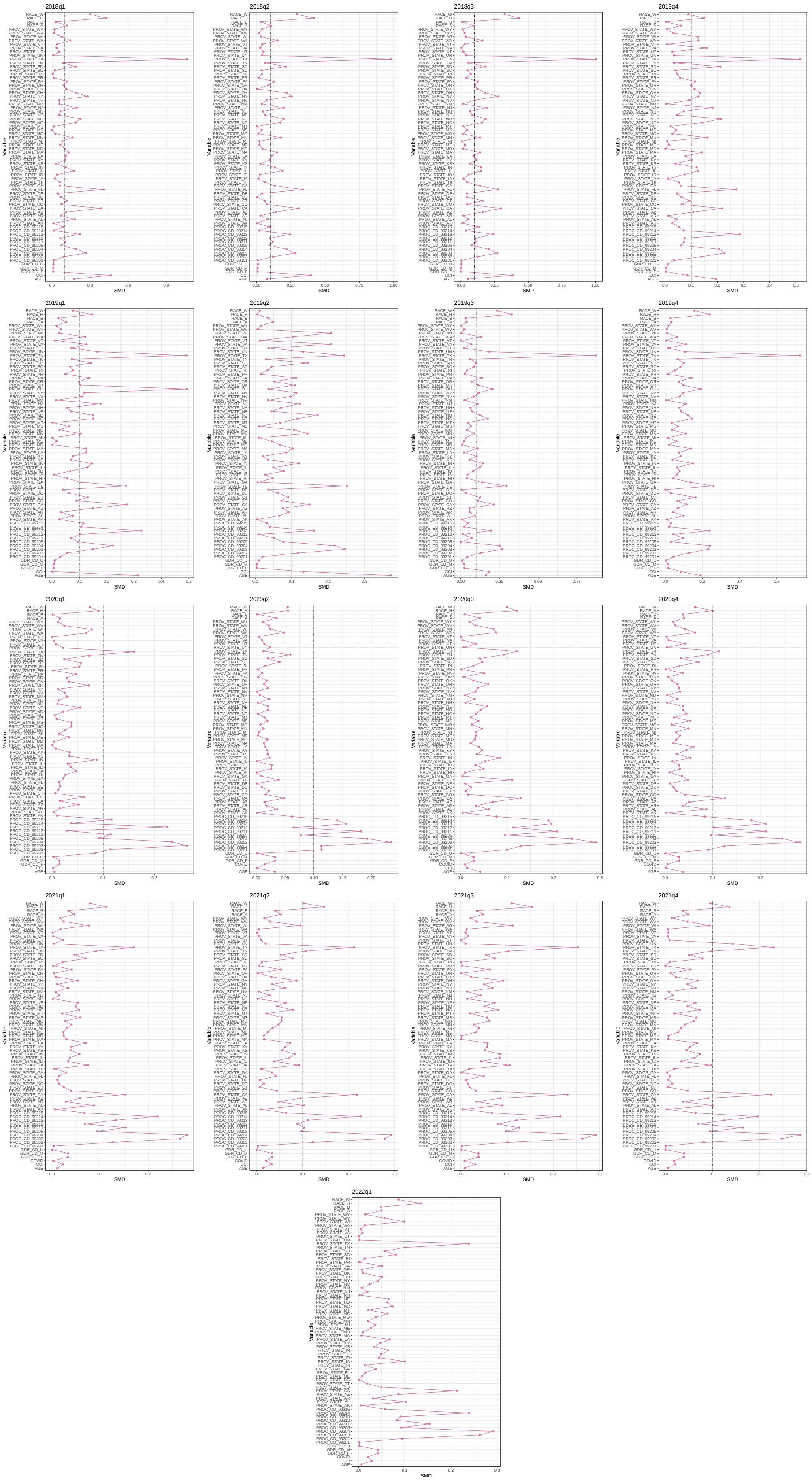


Figure C6: Balance of Covariates Above or Equal to and Below Median Provider Propensity to Use Telehealth, 2018q1 to 2022q1

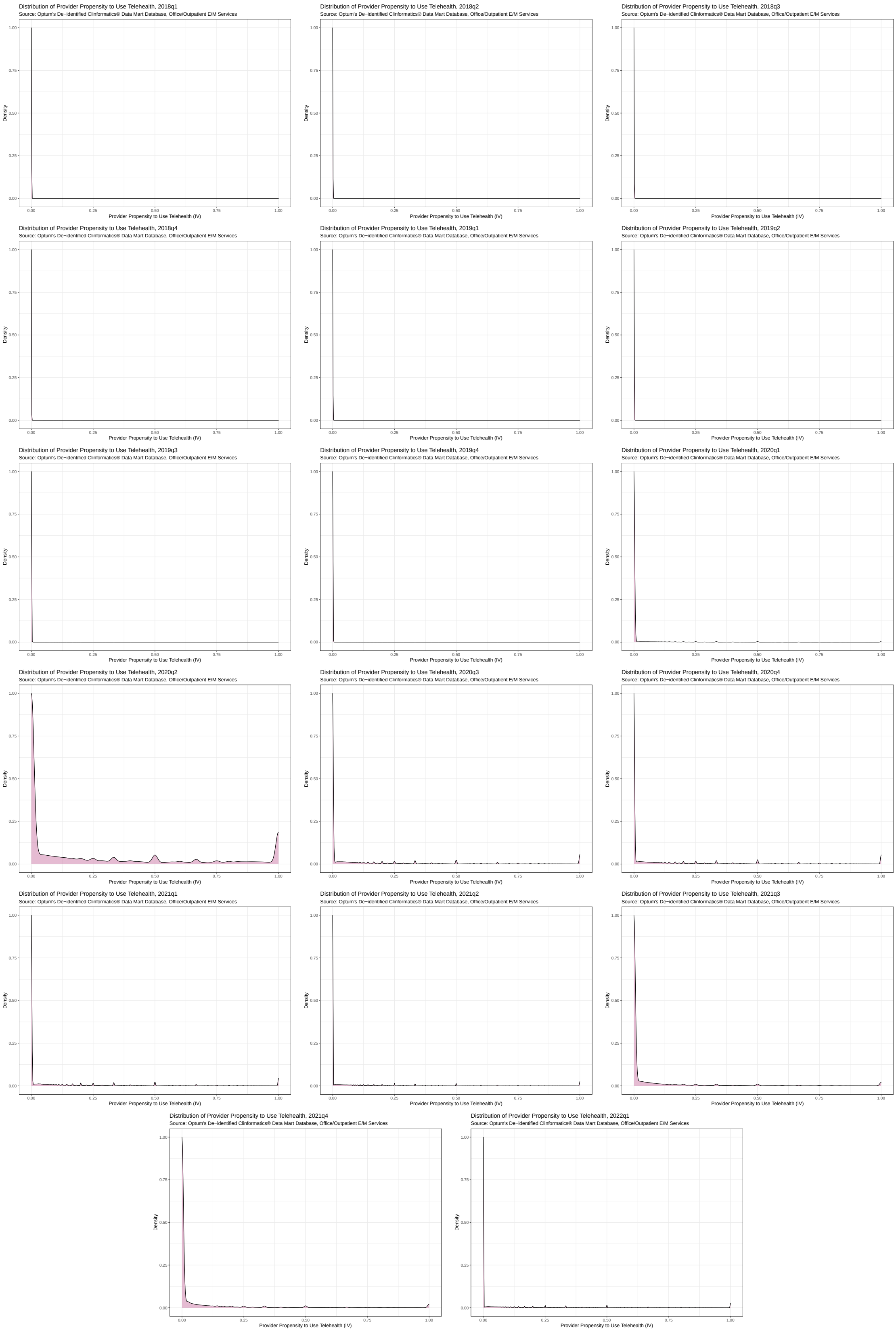


Figure C7: Instrument Distribution, 2018q1 to 2022q1

C.3 Sensitivity Analyses

To support the conclusions from the main results in Section 5, I include additional sensitivity checks in this section where I limit analyses to continuously enrolled patients, limit by patient and provider variation in telehealth usage, and discuss additional factors that could lead to bias.

C.3.1 Continuous Enrollment

In the main results of this paper, I use telehealth and face-to-face office/outpatient E/M service claims for any patients contained in Optum's de-identified Clinformatics® Data Mart Database. However, if some patients are not enrolled in any insurance plan while others are, then constructing Charlson Comorbidity Indices with a four-quarter look-back period could create bias if patients do not have observed chronic conditions and other diagnoses simply because they were not enrolled continuously.

As a sensitivity check, I limit the sample of observations only to those where patients had continuous enrollment for the previous four quarters leading up to the quarter of encounter where an office/outpatient E/M service claim is observed. I re-run the encounter, patient, and provider levels of analysis as specified in Section 4.1. Upon obtaining these results, I find little difference in trends and magnitudes between the main specification and the specification where only patients with continuous enrollment in the four-quarter look-back period for CCI construction are allowed. Table C1 shows a comparison of the post-March 2020 mean average marginal effects by level of analysis and health outcome. Full results are displayed in Figure C8.

Table C1: Post-March 2020 Mean Impacts, Full Sample and Continuously Enrolled Patients

Severe Health Outcome	Level	Measure	Full	Cont. Enroll.
Death (6-Month)	Encounter	AME	4.4	3.9
ER Visit (6-Month)	Encounter	AME	13.0	12.0
Death (6-Month)	Patient	AME	4.9	4.3
ER Visit (6-Month)	Patient	AME	13.3	12.2
Death Rate (6-Month)	Provider (by Visit)	% Δ	21%	23%
ER Visit Rate (6-Month)	Provider (by Visit)	% Δ	6%	6%
Death Rate (6-Month)	Provider (by Patient)	% Δ	24%	26%
ER Visit Rate (6-Month)	Provider (by Patient)	% Δ	4%	4%

Note: AMEs are reported per 1,000 encounters or patients based on level of analysis. Provider visit rates are either aggregated by all monthly visits or patients of a provider.
Source: Optum's De-identified Clinformatics® Data Mart Database

C.3.2 Telehealth Variation by Patient

In the main results of this paper, I include all telehealth and face-to-face office/outpatient E/M service encounters. At the patient level of analysis, to test the impact of telehealth usage on severe health outcomes, I aggregate to monthly shares of telehealth usage by patient. This creates three types of patients: patients who only receive face-to-face services, patients who only receive telehealth services, and patients who receive a mix of telehealth and face-to-face

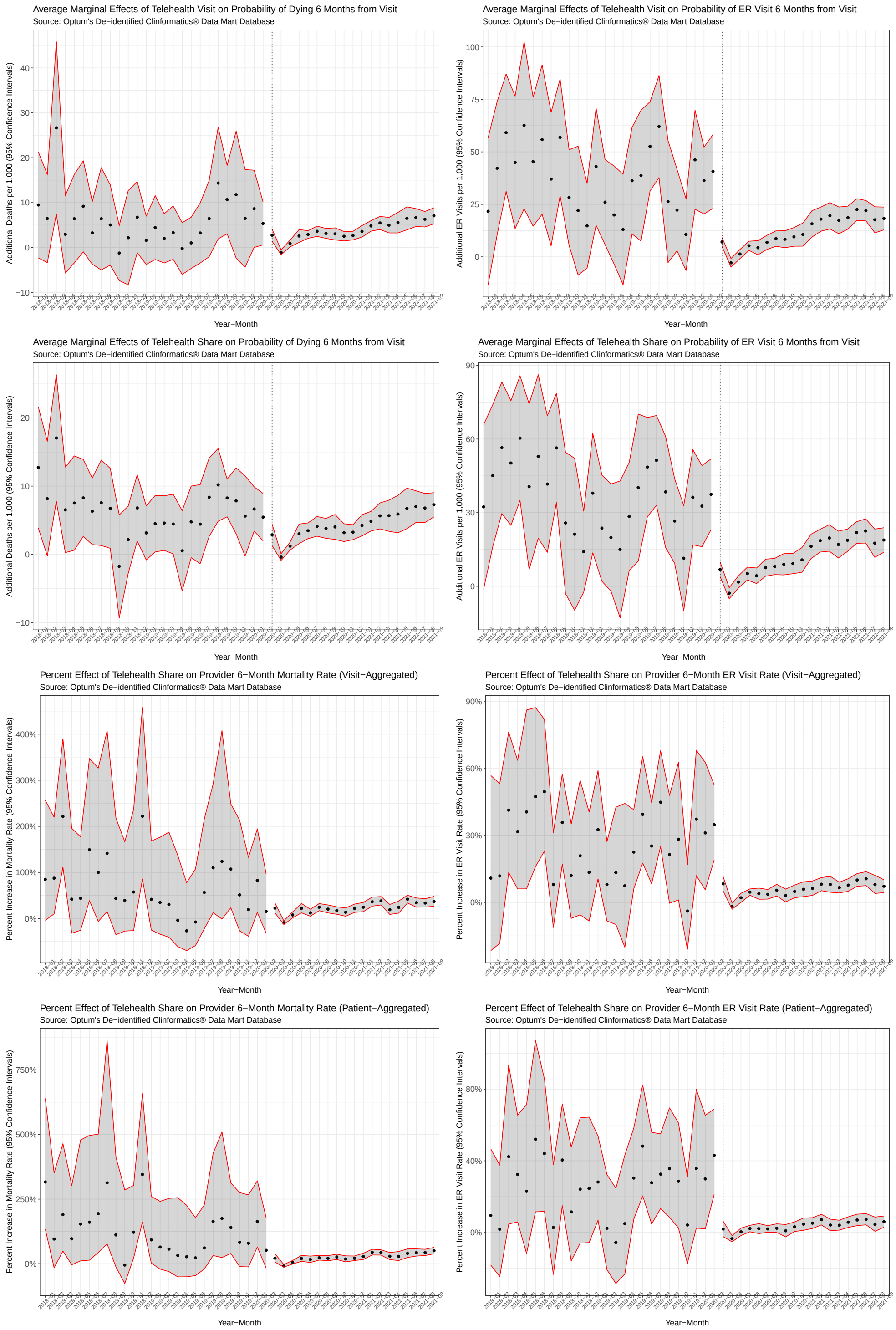


Figure C8: Reduced-Form Estimation Results using Continuously Enrolled Patients

services. In the main results, patients only using telehealth and patients who use a mixture of telehealth and face-to-face care are included in the main analysis.

However, it might be the case that the impact of telehealth usage is not equivalent across telehealth-only and telehealth-mix patients. To test this, I run the patient-level analysis for likelihood of mortality and ER visits, but to obtain the differential impacts of telehealth usage, I separate out telehealth-only and telehealth-mix patients and test separately against face-to-face-only patients. If the results are similar across specifications, then the impacts of telehealth usage may have a monotonic relationship with degree of telehealth usage, regardless if there is additional face-to-face office/outpatient E/M service visits. If the results differ, then it may be that the monthly mixture of visit modality possesses a discontinuity in magnitude of impact on health outcomes.

Figure C9 shows the monthly patient counts by each category of variation in telehealth usage. At the beginning of the COVID-19 pandemic, telehealth usage is largely driven by patients who are only using telehealth. As time progresses, there is a decline in patients who exclusively use telehealth, such that patients who use telehealth either as a mixture of overall care or exclusively are similar in number by the middle of 2021.

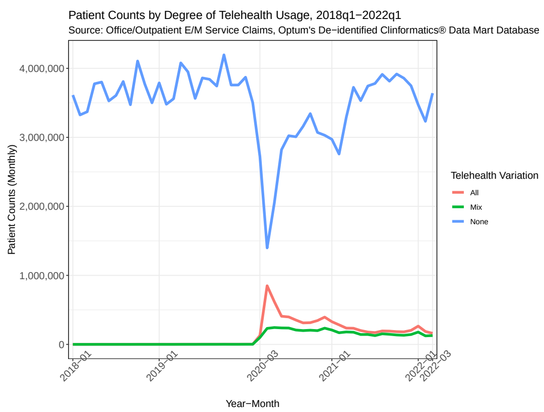


Figure C9: Monthly Patient Counts by Level of Telehealth Usage

I find that estimates of telehealth impact on health outcomes are similar across specifications partitioned by telehealth-only and telehealth-mix patients. Relative to face-to-face only patients, telehealth usage, whether as a mix of all monthly services or as the only form of care received, is generally associated with higher likelihood of severe health outcomes, with exception in the April 2020 cohort as mentioned in the main results. To the extent that there is a differential impact, it appears that telehealth-mix patients have higher estimated average marginal effects, most notably for likelihood of ER visit. However, since ER visits can occur more than once, this could reflect a limitation of looking at the incidence of at least one ER visit within 6 months across both telehealth-only and telehealth-mix patients. Figures C10 and C11 display these results for the post-March 2020 cohorts.

C.3.3 Telehealth Variation by Provider

In the main analysis, across encounter, patient, and provider levels, I allow observations to include office/outpatient E/M service claims from all providers. Providers vary in their level of telehealth usage prior to and during the COVID-19 pandemic, as shown with detail in Section 3.2. While some providers use telehealth frequently or relatively often, other providers may only use telehealth rarely or not at all. It might be expected that the impacts of telehealth usage on health outcomes could be quite different depending on degree of provider use.

Another important consideration is the extent to which evolving billing practices for tele-

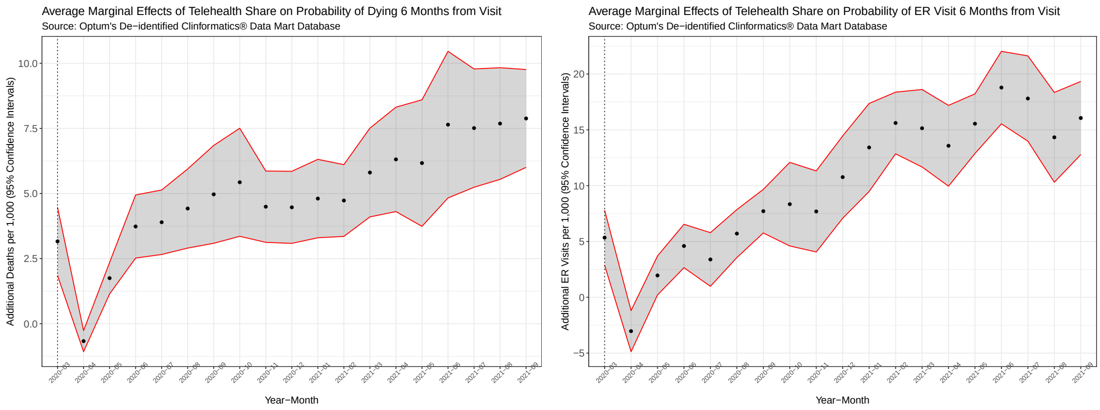


Figure C10: Patient-Level Reduced-Form Estimation Results, Only Telehealth

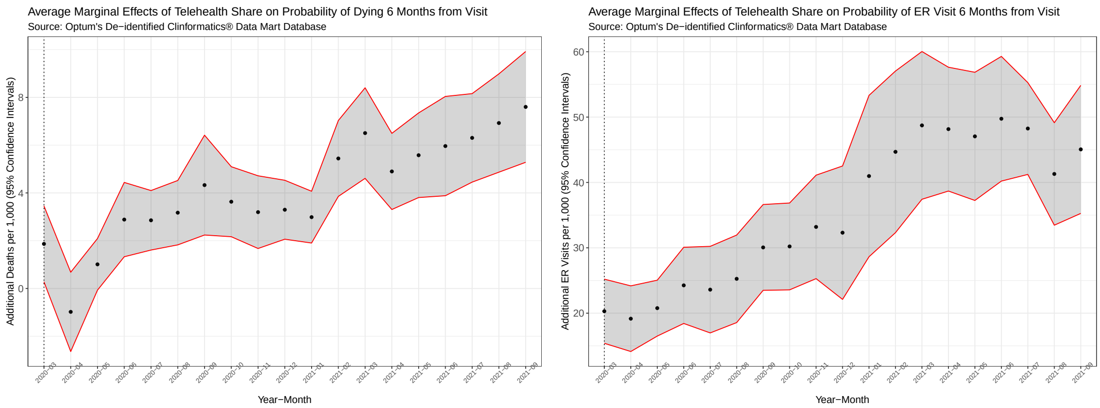


Figure C11: Patient-Level Reduced-Form Estimation Results, Mix of Telehealth

health services may have been an obstacle for health care providers at the onset of the COVID-19 pandemic. As Brotman and Kotloff (2021) document the changes in telehealth billing in evaluation and management services during the COVID-19 pandemic in the United States, there is additional literature such as Sisk et al. (2020) and Bajowala et al. (2020) documenting the frustration and confusion that health care providers may have experienced in telehealth billing due to differences in reimbursement practices and regulation.

For these reasons, comparing encounters from all kinds of providers may produce results that are biased on the true impact of telehealth usage if the variation that providers billed for telehealth services is an indicator of differential impact. In the main results, I use data from one large US insurer through Optum's de-identified Clinformatics® Data Mart Database, as well as accounting for state variation through provider state fixed effects and clustering standard errors. However, providers may still be impacted by degree of telehealth usage within payer and state of operation. To account for this, I run the encounter analysis limited only to face-to-face and telehealth observations from providers who use telehealth at least once in the month of analysis. In doing so, I am comparing telehealth and face-to-face care within telehealth-using providers. I find that the trends and magnitudes of average marginal effects of telehealth usage on likelihood of mortality or ER visit are similar to the main results. The post-March 2020 results are depicted in Figure C12.

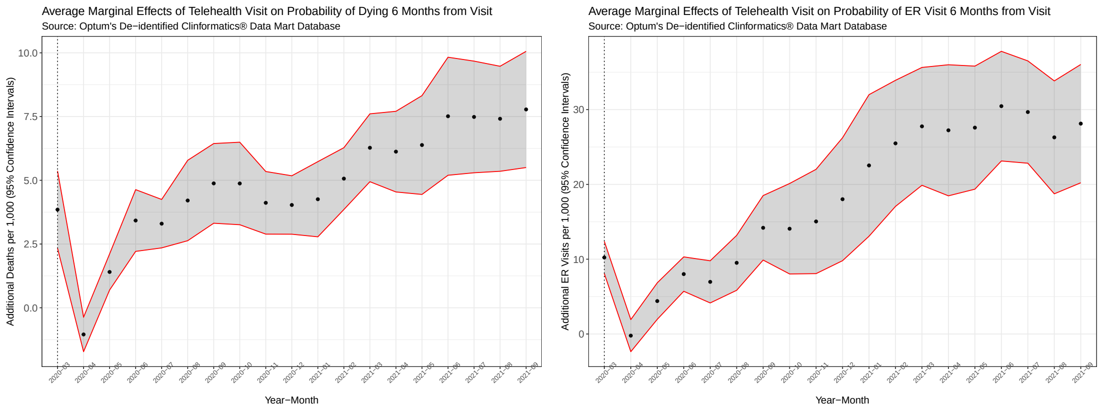


Figure C12: Encounter-Level Reduced-Form Estimation Results, Providers Using Telehealth Only

C.3.4 Reimbursement Rates

There may be a concern that telehealth and face-to-face visits may have varied in reimbursement rates, such that the difference in visit modality is due to a difference in financial incentives. To deal with this, I check whether telehealth usage contributes to a higher or lower standard cost (estimated allowed amount) between 2018q1 and 2022q1 by using OLS to regress cost on telehealth usage. I also allow for CPT® code and provider state fixed effects to capture the effect within the same E/M services and geographies.

Figure C13 displays the estimated difference in standard cost arising from telehealth usage for each quarter of data for the full set claims as well as heterogeneous effects by payer. For most quarters, the difference is not statistically different from zero. Where there is a non-zero estimated difference, it is largest in the three quarters preceding the onset of the COVID-19 pandemic in the US: 2019q2 through 2019q4. Across quarters with a non-zero difference, the estimates range between a \$2.50 to a \$15.00 decrease in cost for telehealth claims compared to face-to-face claims. Not only does this difference appear rather small, it also suggests that telehealth patients on average would have the same reimbursement rates, if not slightly less, than if they had visited in person. However, it also appears that this difference is almost entirely generated by patients enrolled in Medicare Advantage plans.

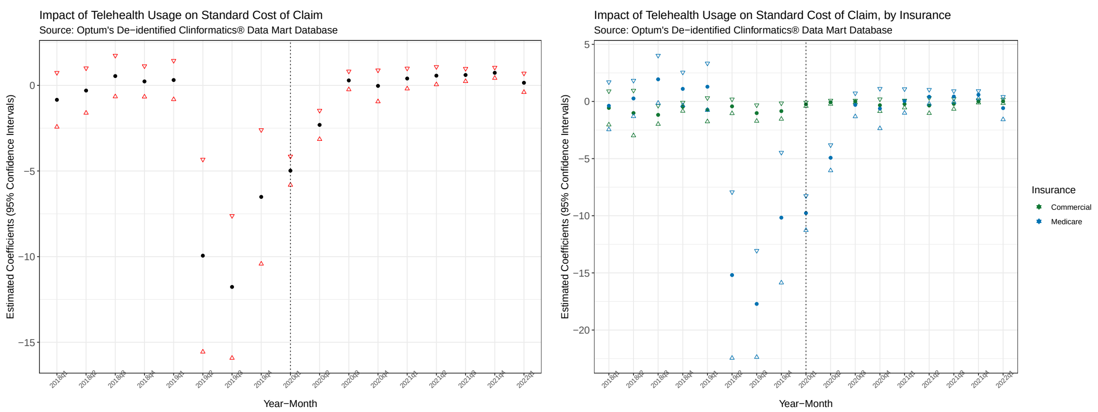


Figure C13: Telehealth and Standard Cost, Overall and by Insurance Type

If telehealth usage induced higher reimbursement rates, it could follow that providers were incentivized to use telehealth more frequently than clinically or medically justified, thus leading to undesirable outcomes. However, since telehealth usage is associated with similar and sometimes lower reimbursement rates, the worst case scenario suggests that providers would have the incentive to use telehealth as little as possible for the services studied here. In addition, where we may be concerned regarding payment parity for commercial providers, Figure C13 shows that commercial providers are reimbursed similarly and not driving the overall trend. Thus, while there are slight differences in certain quarters in allowed amounts, I do not believe these differences lead to a concern regarding selection bias.

C.3.5 Charlson Comorbidity Index (CCI)

We might have concern that telehealth usage is correlated with a patient's health status. For instance, if providers prefer to see patients in person, only patients who are sufficiently unwell will have a telehealth appointment. On the other hand, providers might use telehealth only to meet with the healthiest of patients and leave in-person visits for patients at most risk. Given that the reduced-form empirical results suggest telehealth usage is associated with higher likelihood of severe health outcomes, I am most concerned with the bias from the first case.

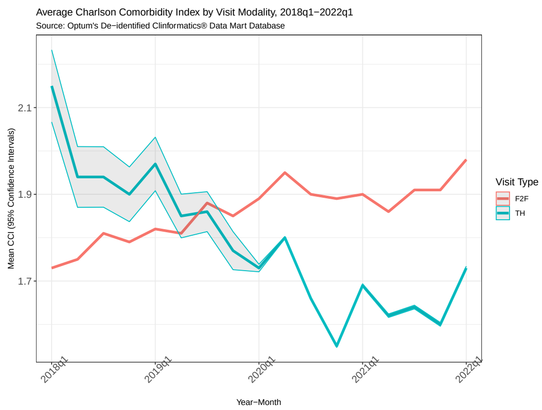


Figure C14: Trends in CCI by Visit Modality

First, I obtain the trends in measured health risk across time by using Charlson Comorbidity Index (CCI) scores. To construct Charlson Comorbidity Index measures for each patient, I follow the algorithm outlined by Quan et al. (2005) for ICD-10 diagnosis codes using a four-quarter look-back period for patients. Figure C14 displays the mean Charlson Comorbidity Index for each quarter from 2018q1 to 2022q1. This graph actually suggests that prior to the COVID-19 pandemic, telehealth patients on average had higher health risk measured through comorbidities. However, in the middle of 2019, this began to change. From the onset of the pandemic onward, telehealth patients had lower health risk measured through CCI on average.

To be more robust by conditioning on covariates, I test whether higher CCI scores are associated with telehealth usage at the encounter level. I perform logistic regression using the same set of covariates and fixed effects as in the reduced-form specification in the main results of this paper. Figure C15 shows the estimated coefficients and the average marginal effects by month-year cohort for this test. Prior to March 2020, there is a positive relationship between a patient's CCI and the likelihood of telehealth usage, which is in line with the overall average trends in Figure C14. However, since telehealth usage was so rare, the average marginal effects are infinitesimal. Upon March 2020 and after, the estimated coefficients decline toward zero, and many cohorts observe confidence intervals that overlap with zero. Since telehealth usage is much more frequent post-March 2020, the marginal effects appear slightly larger than pre-COVID-19. However, the marginal effects are still extremely small when significant, and in many cases there is a null effect.

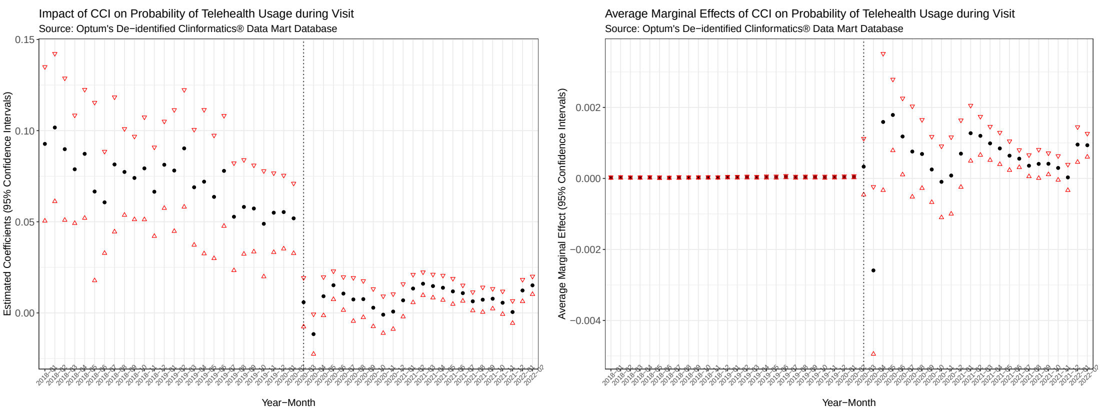


Figure C15: CCI and Telehealth Usage, Impacts and Average Marginal Effects

From the overall average trends combined with the presence of many null effects across months post-March 2020, I conclude that there is little to suggest telehealth usage is systematically more likely when patients are more sick. Nevertheless, I include CCI as a covariate in my empirical analysis to control for underlying health status, along with patient age and COVID-19 diagnosis.

C.3.6 COVID-19 Diagnosis

In the main specification of the paper, I account for COVID-19 diagnosis by checking if COVID-19 was diagnosed at the time of the E/M service claim using the following criteria over ICD-10 diagnosis codes:

- Any of diagnosis codes B97.29, J12.89, J20.8, J22, J40, J80, J98.8 diagnosed on or after 2/20/20
- (OR) U07.1, U07.2, U07.3 diagnosed on or after 2/1/20
- (OR) Z03.818, Z11.59, Z20.828 diagnosed on or after 4/1/20
- (OR) J12.182, Z11.52, Z86.16, Z20.822, M 35.81, M35.89 on or after 1/1/21
- (OR) U09.9 on or after 06/30/21

However, there may be concern that someone with or without a COVID-19 diagnosis at the time of an E/M service claim experienced a COVID-19-related severe health outcome within the 6-month window. More directly, we may be concerned that effects of telehealth usage are driven by patients who contracted COVID-19. Given the context of the COVID-19 pandemic, it is entirely possible that providers and patients mostly used telemedicine when patients had or were likely to have COVID-19 at the time of appointment, and thus the relationship between telehealth usage and severe health outcomes could be driven by COVID-19 rather than the visit modality itself.

I address this concern in a set of steps. First, I look at the evolution of office and outpatient E/M visits by claims with COVID-19 diagnoses versus those without. Figure C16 illustrates this evolution, revealing that the majority of visits with an observed COVID-19 diagnosis are face-to-face rather than telehealth appointments.

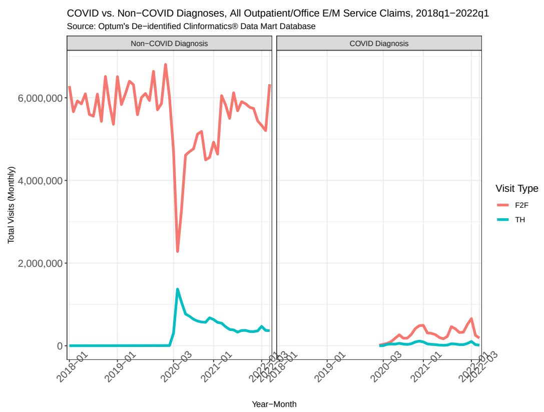


Figure C16: Telehealth vs. Face-to-Face Trends by COVID-19 Diagnosis

While this is true overall, I use a logistic regression to check whether having a COVID-19 diagnosis is associated with higher likelihood of telehealth usage when conditioned on age, CCI, and other demographic and visit controls used in the main empirical analysis. Figure C17 shows that COVID diagnoses on claims are often associated with higher likelihood of telehealth usage, with average marginal effects between 0.02 and 0.09 in 2020 alone. There is a decline following 2020, but, overall, I find there is positive association with COVID-19 diagnosis and telehealth usage rather than face-to-face usage, conditional on demographic, health status, and visit controls.

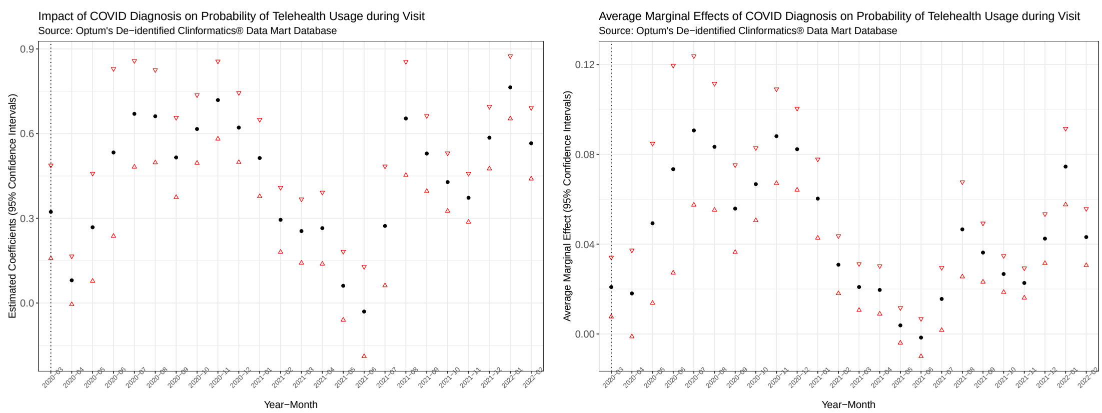


Figure C17: COVID-19 and Telehealth Usage, Impacts and Average Marginal Effects

If patients with COVID-19 diagnoses are more likely to experience telehealth as a visit modality, how do COVID-19 diagnoses impact severe health outcomes? Here, we use the empirical results at the encounter, patient, and provider level to examine how a COVID-19 diagnosis impacts likelihood of a severe health outcome within 6 months of visit.

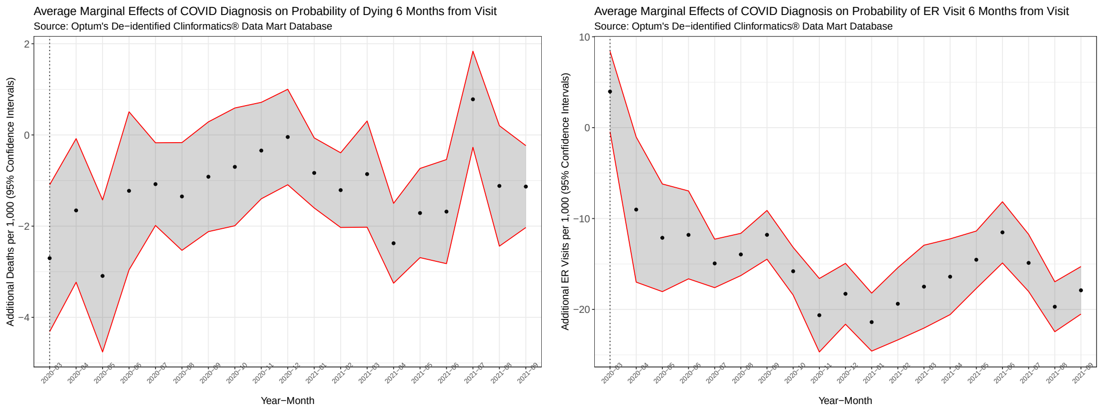


Figure C18: Encounter-Level Reduced-Form Estimation Results, COVID-19

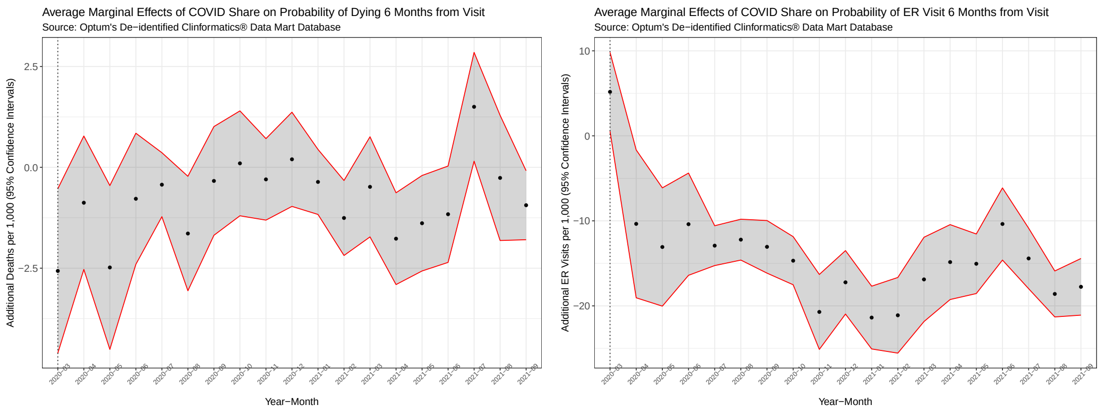


Figure C19: Patient-Level Reduced-Form Estimation Results, COVID-19

Figures C18 and C19 show the average marginal effects by year-month cohort of COVID-19 diagnosis at the time of visit on severe health outcomes within 6 months at encounter and patient levels. In all cases, there is either a null impact or a negative association between COVID-19 diagnosis and likelihood of severe health outcome. For deaths within 6 months, COVID-19 appears to have a null or small negative effect on likelihood, whereas for ER visits within 6 months, COVID-19 has a larger negative effect. It may initially appear concerning that there is an observed decrease in likelihood of severe health outcome associated with a COVID-19 diagnosis. However, it must be remembered that for these data, diagnoses are observed only when care is received. Thus, conditional on receiving care, along with controlling for the aforementioned factors, I find one is less likely to experience any severe health outcome upon having COVID-19.

Nevertheless, we may still be concerned that higher likelihood of severe health outcomes associated with telehealth usage are driven by COVID-19-related outcomes, even after controlling for COVID-19 diagnosis at the time of office/outpatient E/M service claim. To account for this, I use COVID-19 diagnosis data to partition severe health outcomes into COVID-19 and non-COVID-19 ER visits and deaths. For this process, I categorize the first ER visit observed within the 6-month window as a COVID-19 outcome if there is a COVID-19 diagnosis associated with the claim and a non-COVID-19 outcome otherwise. For individual mortality, categorization is more complicated, since a death is not necessarily associated with a particular claim. Instead, I check if the last COVID-19 diagnosis associated with a patient who has a date of death falls in the same month or the month prior to their death.

Once severe health outcomes are categorized, I rerun the encounter-level analysis for both outcome types. Figures C20 and C21 display the results for March 2020 and onward. What I find is that after controlling for COVID-19 diagnosis at the time of claim, as well as the remaining covariates related to patient, provider, and visit characteristics, the average marginal effects of telehealth usage on health outcomes are positive and significant for both COVID-19 and non-COVID-19 health outcomes, with April 2020 as the general exception.

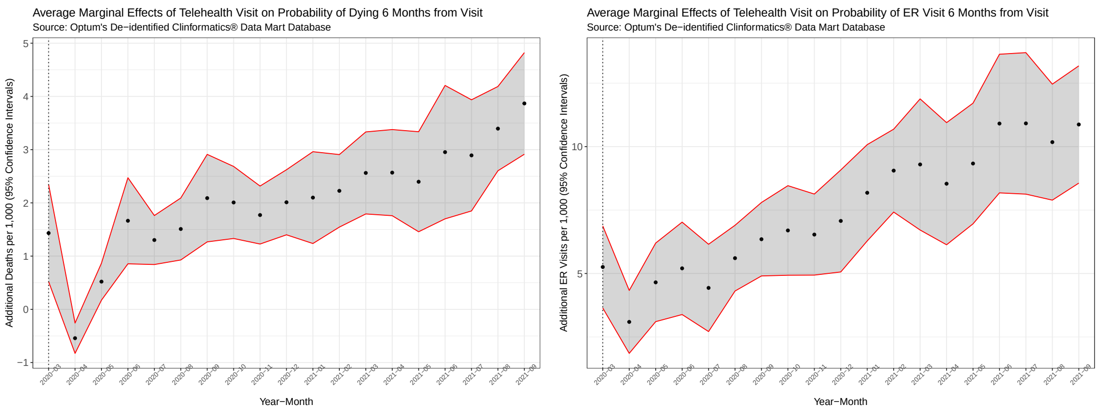


Figure C20: Encounter-Level Reduced-Form Estimation Results, COVID-19 Severe Health Outcomes

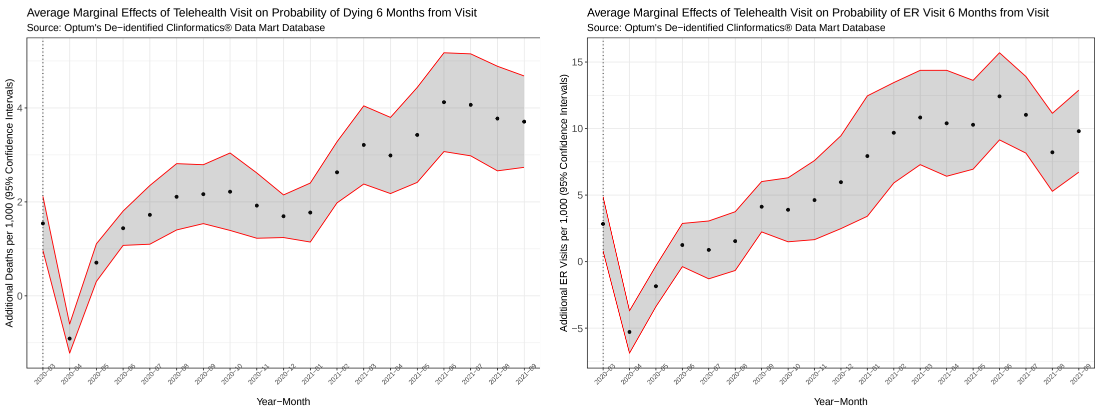


Figure C21: Encounter-Level Reduced-Form Estimation Results, Non-COVID-19 Severe Health Outcomes

I conclude with the finding that while telehealth usage and COVID-19 diagnoses are positively associated with each other, and while telehealth usage is associated with higher likelihood of COVID-19-related severe health outcomes relative to in-person visits, the effects on non-COVID-19 outcomes demonstrate that COVID-19 diagnoses and outcomes alone are not responsible for the effects found in the main results of this paper. The additional work in this section of the appendix supports the main reduced-form results where I account for the role that COVID-19 diagnoses play by including an indicator for COVID-19 diagnosis at the time of visit.

C.4 Standard Errors

Following Abadie et al. (2022), I cluster standard errors at the provider state level. For models with fixed effects, this is justified when there is heterogeneity in the treatment effects and either clustering in the sampling or assignment process. Given that telehealth usage across states may have differed due to both evolving health care policy throughout the pandemic as well as norms and behaviors for servicing care, state-level clustering is appropriate in this context.