Physician Information Costs and the Rise of Telehealth during the COVID-19 Pandemic

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May 2023

Abstract

The use of synchronous telemedicine services rose dramatically during the COVID-19 pandemic, but to what extent should telehealth be used going forward? Using 2018-2022q1 claims data from Optum's de-identified Clinformatics® Data Mart Database, I characterize the evolution of telehealth and face-to-face modalities for office and outpatient evaluation and management (E/M) service claims, where telehealth coding has been the most frequent. I find telehealth usage is associated with higher likelihood of patient mortality and ER visit within 6 months of E/M service claim, with strongest impact for Medicare Advantage plan members, for established patients, and for patients with no referring provider. To explain these findings, 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. In doing so, I provide a mechanism to explain differences in health outcomes and quantify differences in information costs across visit modalities. Estimated average increases in physician information costs range between 5 to 29 percent with telehealth usage after March 2020. These findings reinforce existing literature that suggest telehealth is best used when expanding access to care for low-risk patients and as a complement rather than a substitute to in-person care.

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

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

In this paper, I address three key questions. First, how does telehealth usage evolve before and throughout the COVID-19 pandemic across the United States? Second, how does telehealth usage impact patient health outcomes in its most frequent form, that is, when used as a substitute for in-person care? Third, how costly to health care providers are the informational limitations of telehealth as a visit modality relative to in-person care?

Using claims data from Optum's de-identified Clinformatics® Data Mart Database, I 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 insurance plan type for patients 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 effects are most pronounced for patients with Medicare Advantage plans, for established patients, and for patients without a referring provider. 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.

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 or expands access to 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. In doing so, I contribute 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 reduced-form estimation approach as well as the model-based estimation of information costs. Section 5 discusses the results of both 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, we 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 we 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 $\xi \equiv \left(1 - \sigma_{x|s}^2 / \sigma_x^2\right) \in [0, 1]$, such that the optimal

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

attention strategy is characterized as

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

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 $2ra^2\sigma_x^2$. For $\lambda \geq 2ra^2\sigma_x^2$, the optimal attention strategy is $\xi^* = 0$. These implications will be pivotal to the identification strategy in the follow 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, 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, we can derive the rationally inattentive physician's indirect utility function for each regime's attention strategy:

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

[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.

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 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, we 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

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

From Equation 9, we have

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

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

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

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 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 A1 in the appendix 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.

[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.

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.

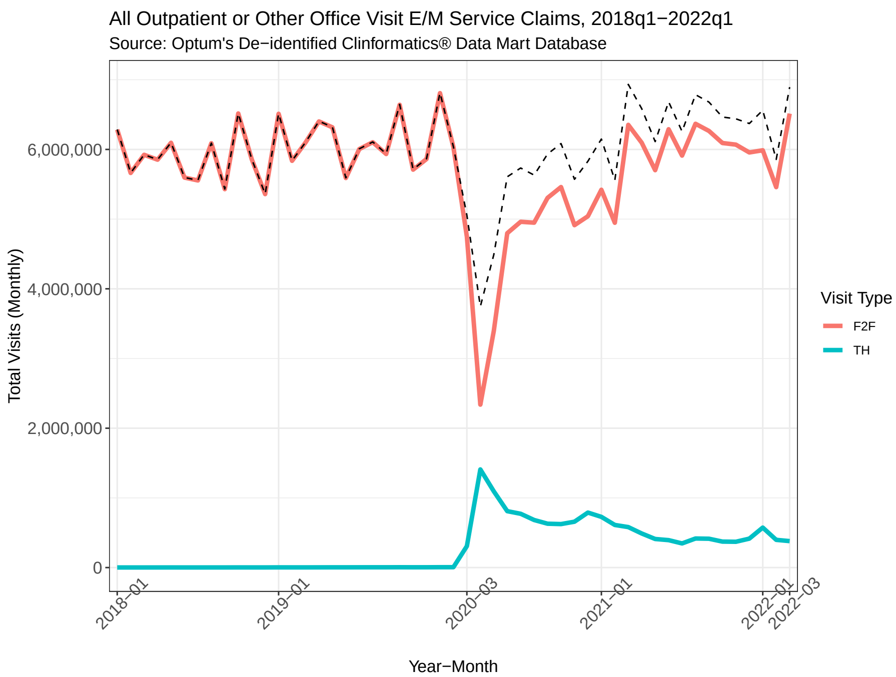


Figure 1: Telehealth vs. Face-to-Face Trends

Overall trends in use come from several types of patients who may differ by purpose in obtaining care or background prior to receiving care. 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. These trends across patient heterogeneity are shown in Figure A1 in the appendix.

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 B7 in the appendix.[5]

Moving from patient-oriented to provider-oriented 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 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 A2 in the appendix.

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.

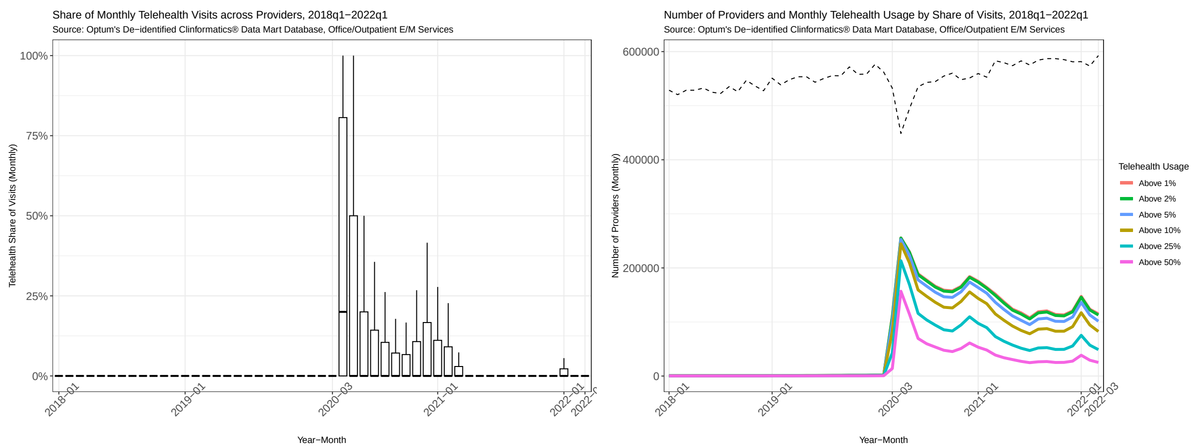


Figure 2: Telehealth Trends by Provider

While it is certainly the case that there are providers with little use of telemedicine in

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

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. Then, 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

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

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

[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.

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 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, we 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

[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.

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

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

In each reduced-form model specification, the desired objective 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:

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

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, we cannot assume that the condition in Equation 15 necessarily holds. In this context, we may instead be exposed 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.

For dealing with this potential bias, 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 the 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. With this approach, I assume conditional independence, or 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, we use our 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.

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 use both inverse propensity score weighting and overlap weighting methods, and a further description of these methods and results can be found in the appendix. I include appendix figures comparing covariate balance across unweighted and weighted groups as well as propensity score distributions by telehealth usage to illustrate common support. In addition, I test the impact of additional factors on telehealth usage as visit modality, and these results are also included in the appendix. Although I am unable to control for unobserved factors and am limited by data and methodology in this way, I find that the additional strategies performed to address the remaining threats to validity ultimately support the results from the empirical framework outlined in this section.

The results from estimating the reduced-form empirical framework are valuable in two main ways. First, these results will provide a justification for investigating differences in 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, as outlined in the following section.

4.2 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

$$\frac{\lambda_{TH} - \lambda_{F2F}}{\lambda_{F2F}} = \frac{\gamma_{TH} \times 2ra^2\sigma_x^2 - \gamma_{F2F} \times 2ra^2\sigma_x^2}{\gamma_{F2F} \times 2ra^2\sigma_x^2} = \frac{\gamma_{TH} - \gamma_{F2F}}{\gamma_{F2F}} \tag{17}$$

and the absolute change in physician information costs as

$$\frac{\lambda_{TH} - \lambda_{F2F}}{2ra^2\sigma_x^2} = \frac{\gamma_{TH} \times 2ra^2\sigma_x^2 - \gamma_{F2F} \times 2ra^2\sigma_x^2}{2ra^2\sigma_x^2} = \gamma_{TH} - \gamma_{F2F} \tag{18}$$

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 17 and 18 from our empirical analysis, we rearrange Equation 6 in terms of γ_M to get

$$\frac{2 * V_M^*}{2ra^2\sigma_x^2} = \gamma_M \log_2(\gamma_M) - \gamma_M \quad \text{where } \gamma_M \in (0,1] \; \forall M \in \{F2F, TH\}. \tag{19}$$

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 19: 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 19 is constrained as depicted in Figure 3, with the vertical line marking $\gamma_M = \exp(\ln(2) - 1)$.

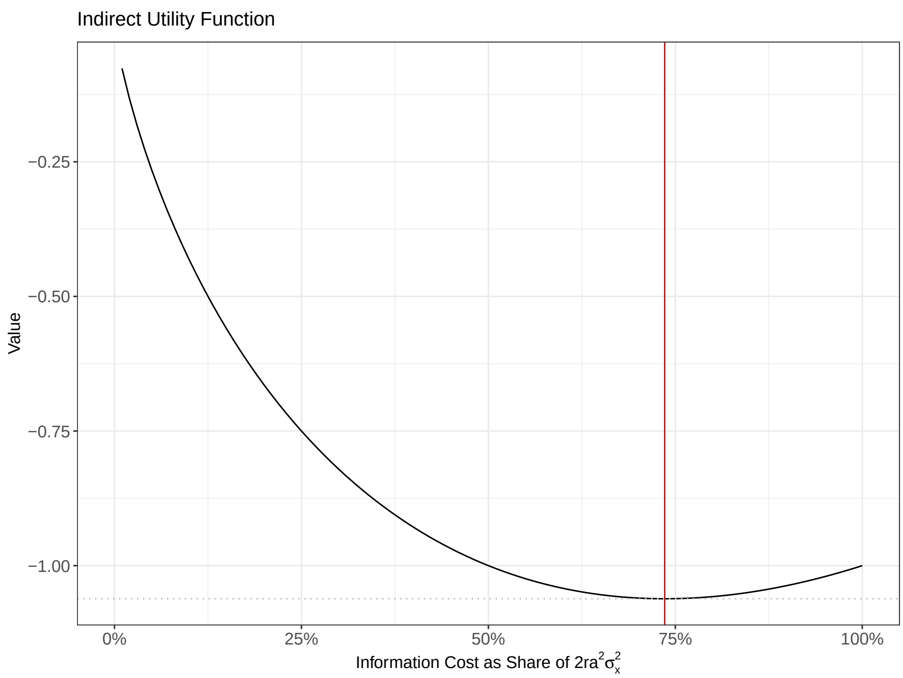


Figure 3: Information Cost and Indirect Utility

Thus, in order to obtain γ_M from Equation 19 using the data, I set

$$\hat{V_M^*} = -\frac{2 * V_M^*}{2ra^2\sigma_x^2} \; \forall M \in \{F2F, TH\}. \tag{20}$$

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 20, 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 19, which will allow us to evaluate changes in information costs represented by Equations 17 and 18. 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 both reduced-form estimation 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 metrics. 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.

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.

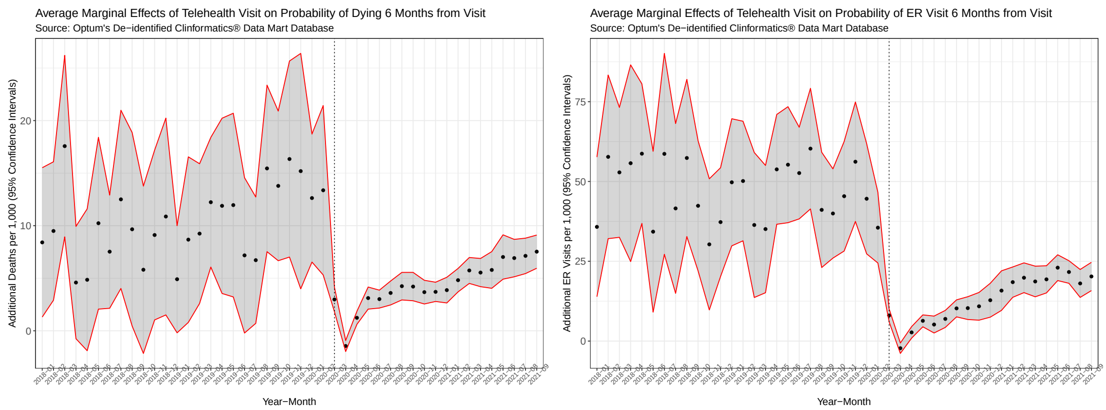


Figure 4: Encounter-Level Reduced-Form Estimation Results

Prior to March 2020, we 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 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 commercial and Medicare Advantage insurance plan members, referred and non-referred patients, and established and new patients. 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. This is likely due to the fact that each of these characteristics 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.

Moreover, 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, these estimates should be seen as a conservative lower bound on overall emergency room utilization associated with telehealth usage.

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.

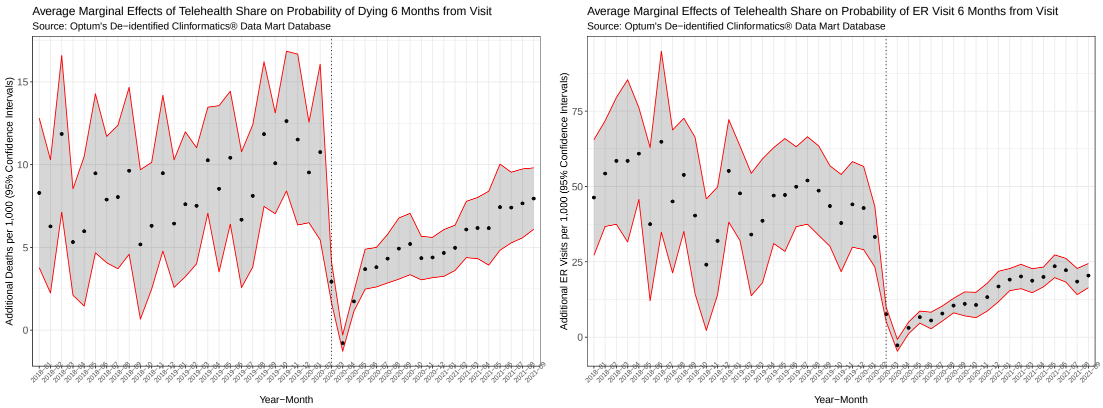


Figure 5: Patient-Level Reduced-Form Estimation Results

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.

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 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

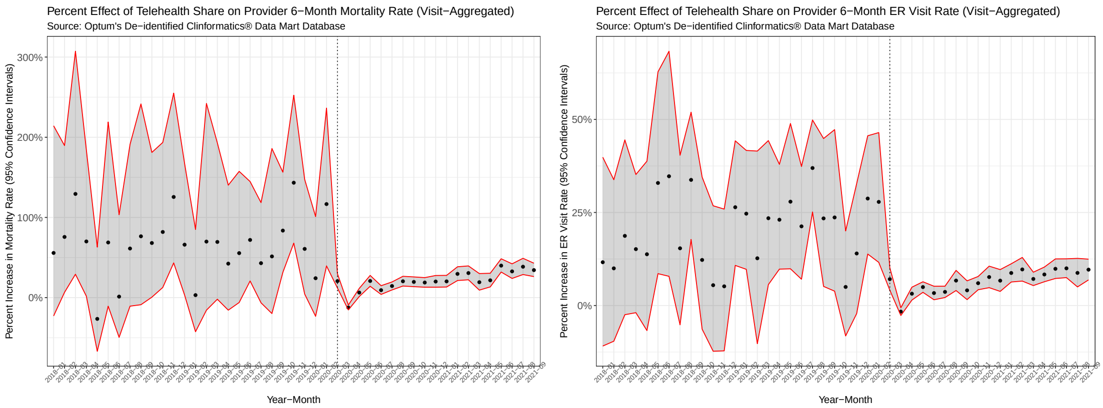


Figure 6: Provider-Level Reduced-Form Estimation Results, Aggregated by Encounter

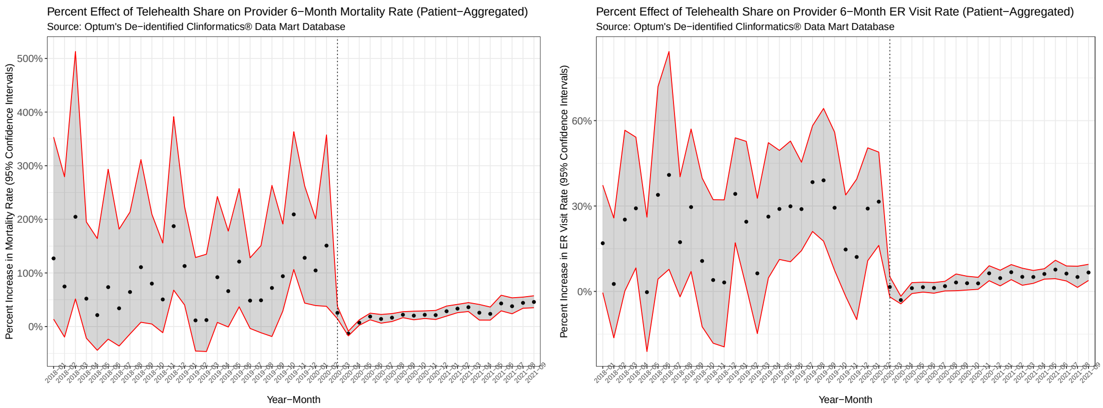


Figure 7: Provider-Level Reduced-Form Estimation Results, Aggregated by Patient

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.

In the appendix, I include additional results from alternative specifications that incorporate propensity scores and weighting strategies, as well as a discussion of factors that may present endogeneity concerns. The results of these robustness checks bolster the main results found in this section. 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, we move to our model calibration and calculation of information costs.

5.2 Estimation of Information Costs

To estimate changes in information costs across visit modalities according to Section 4.2, I obtain $\hat{V_M^*}$ in Equation 20 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

19, 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 8 through 9 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, we see a consistent, nonzero percent increase in physician information costs.

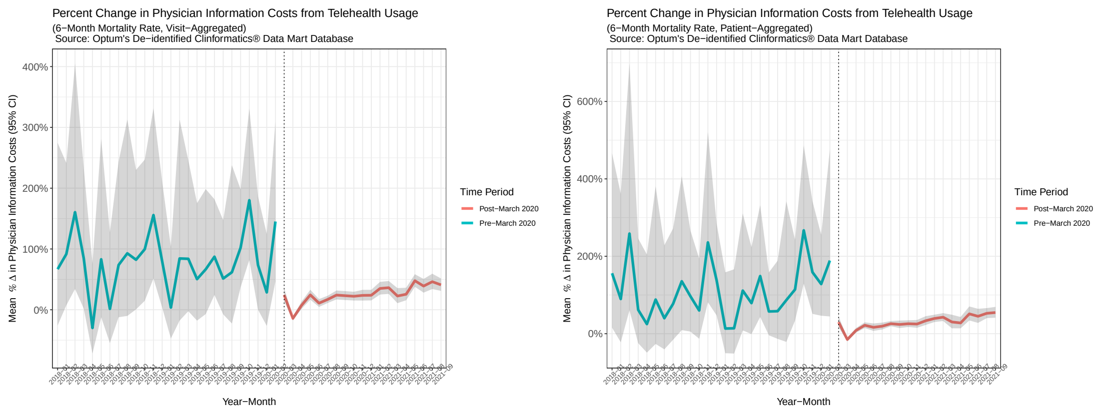


Figure 8: Percent Change in Information Costs, by Mortality Rate

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 the appendix.[9]

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

[9]I also include cohort-level rates of provider 6-month mortality and ER visit aggregated by visit and patient in the appendix.

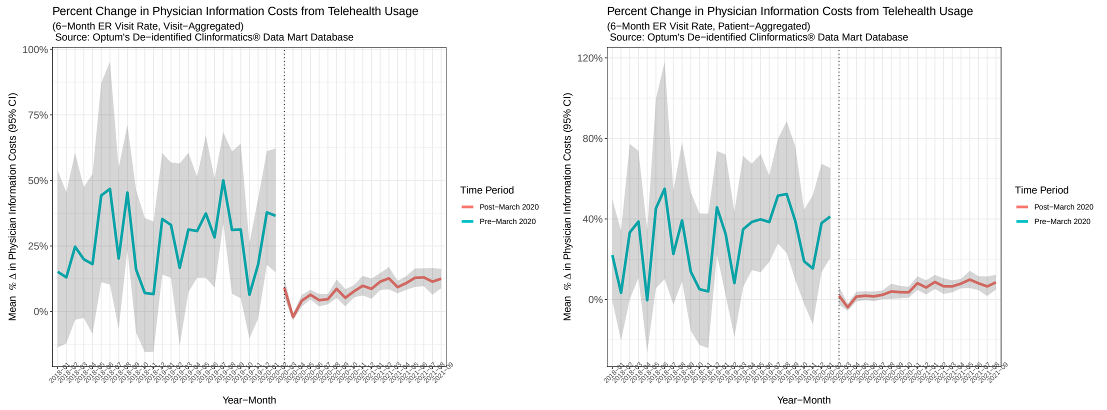


Figure 9: Percent Change in Information Costs, by ER Visit Rate

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. As a result, I cannot guarantee that the selection process for telehealth usage was random, nor do I have data that speaks to this process for this set of claims. While I include strategies to control for observed patient, provider, and encounter characteristics that may contribute to endogeneity, I am limited by the data and research methods used in this paper to reduce these concerns. Future qualitative 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 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.

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.

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., 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.

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.

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

Table A1: 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

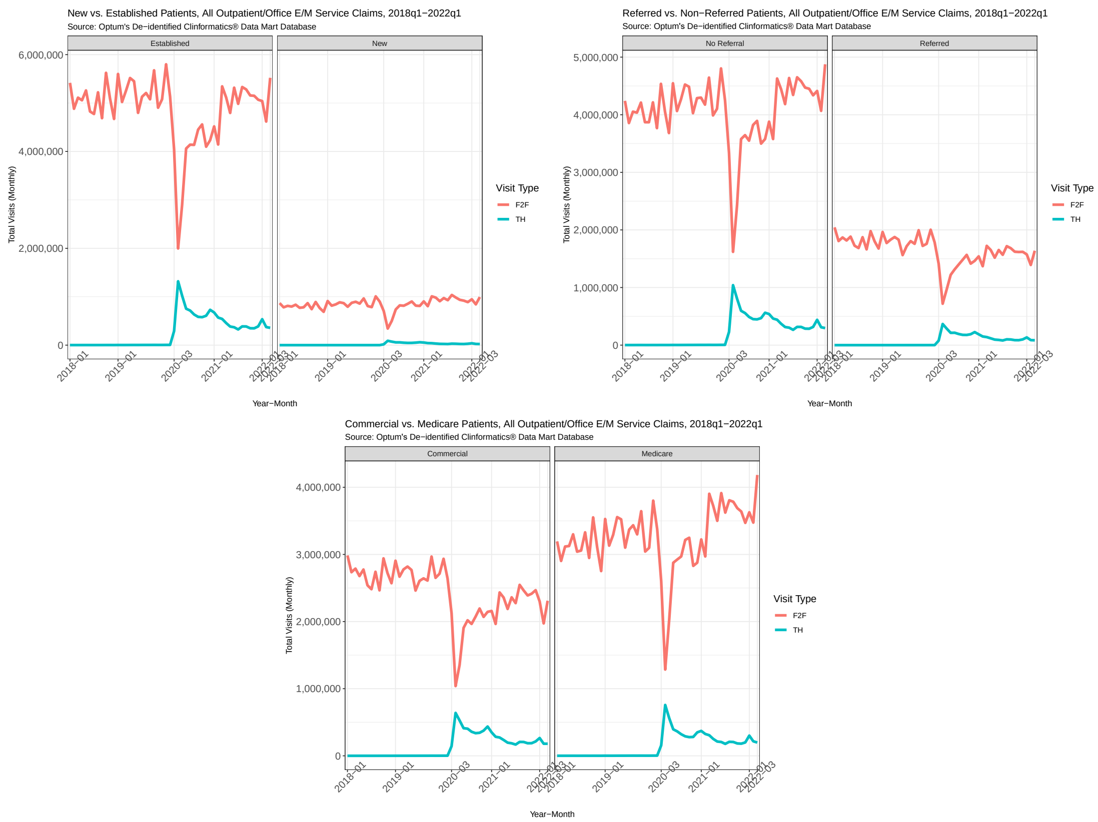
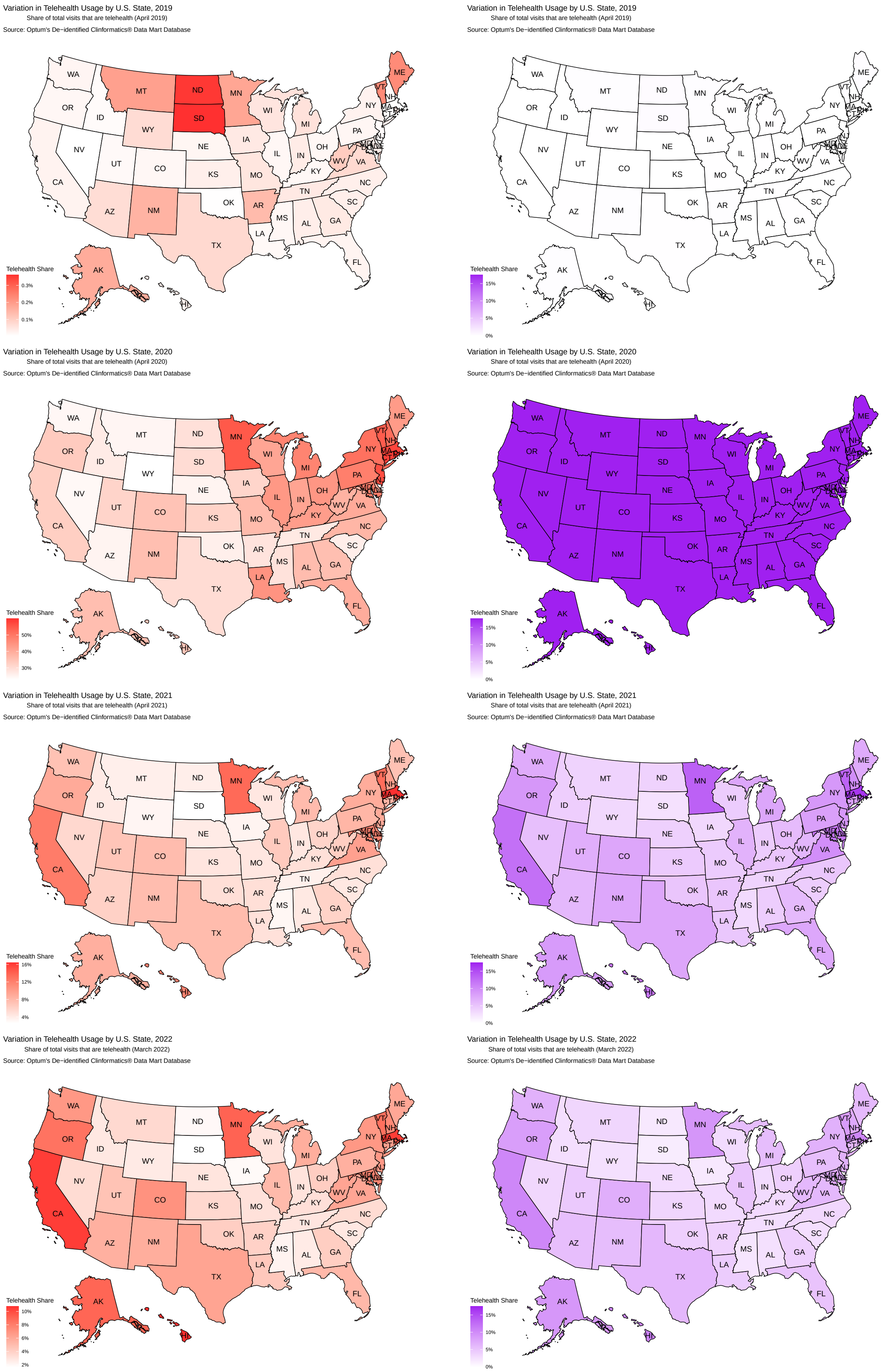


Figure A1: Telehealth vs. Face-to-Face Trends by Patient Type



(A) Differing Scales across Years

(B) Same Scale across Years

Figure A2: Telehealth Trends by Provider State, 2019-2022

Table A2: 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 A3: 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 A4: 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 A5: 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 A6: 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 A7: 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 A8: 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 A9: 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%)

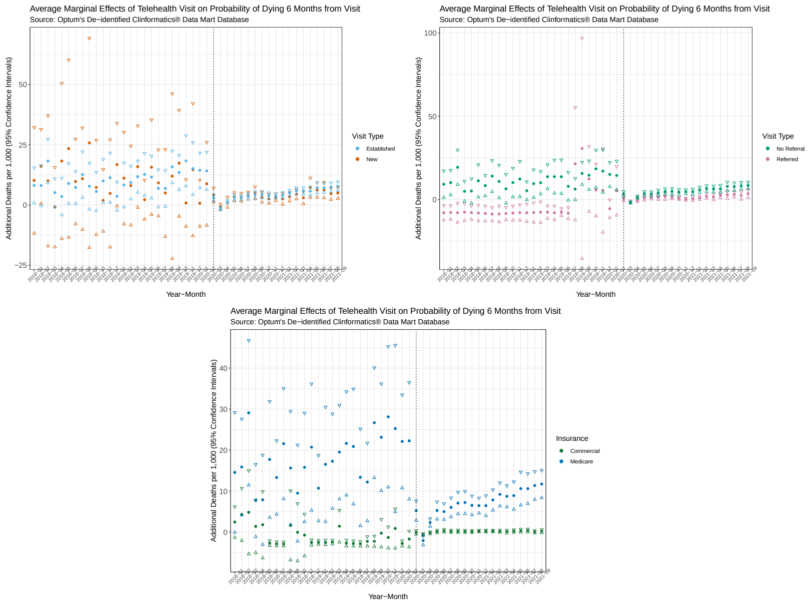


Figure A3: (Mortality) Encounter-Level Reduced-Form Estimation Results, by Patient Heterogeneity

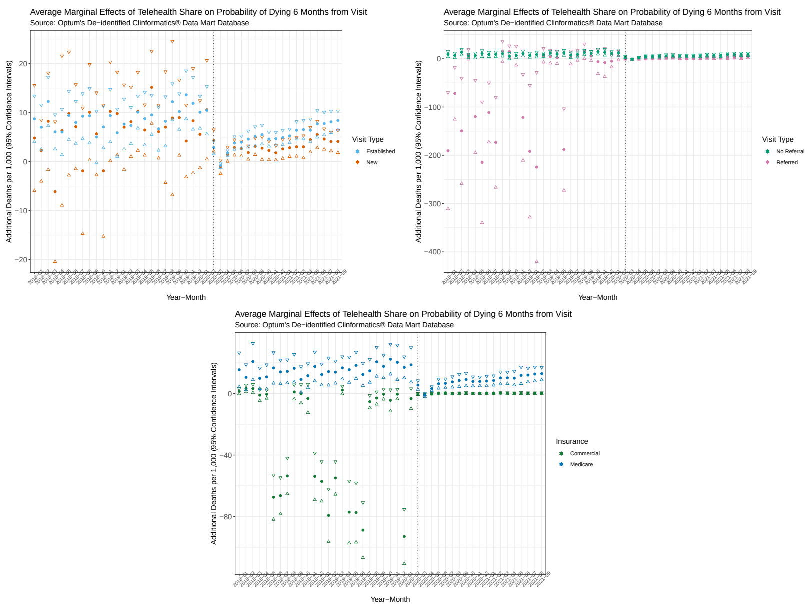


Figure A4: (Mortality) Patient-Level Reduced-Form Estimation Results, by Patient Heterogeneity

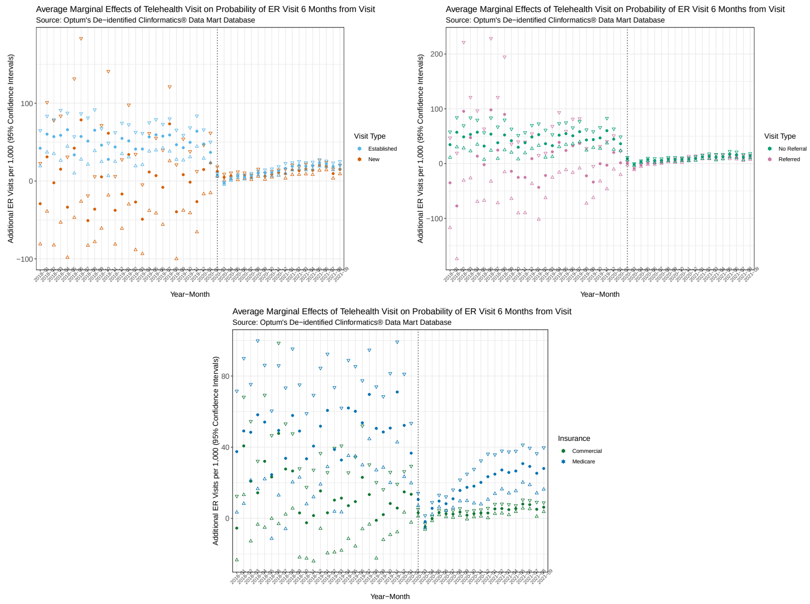


Figure A5: (ER Visit) Encounter-Level Reduced-Form Estimation Results, by Patient Heterogeneity

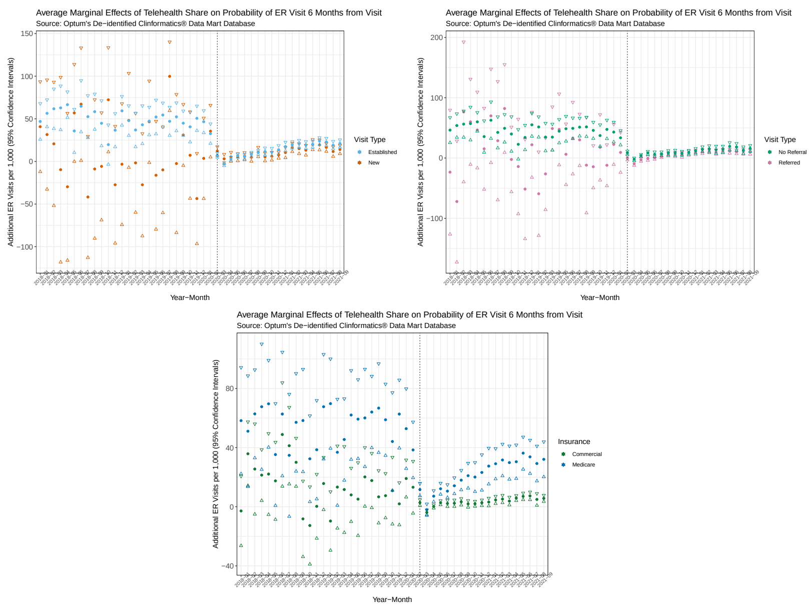


Figure A6: (ER Visit) Patient-Level Reduced-Form Estimation Results, by Patient Heterogeneity

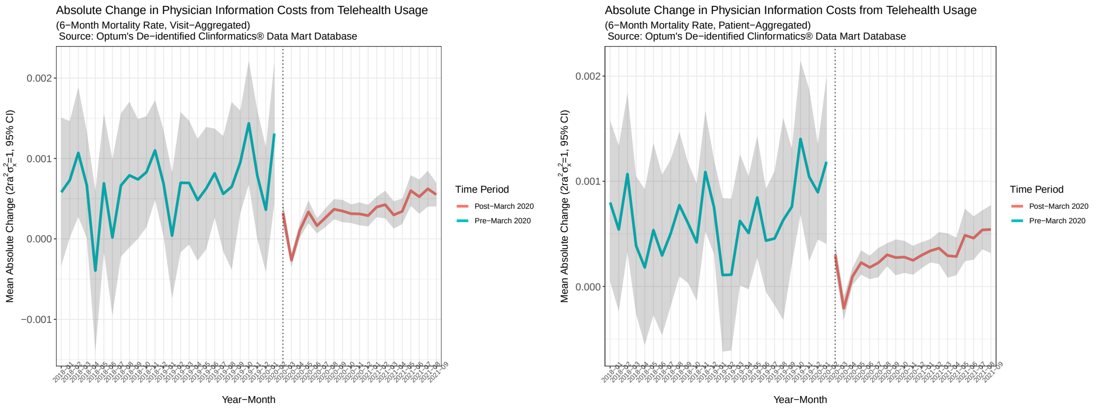


Figure A7: Absolute Change in Information Costs, by Mortality Rate

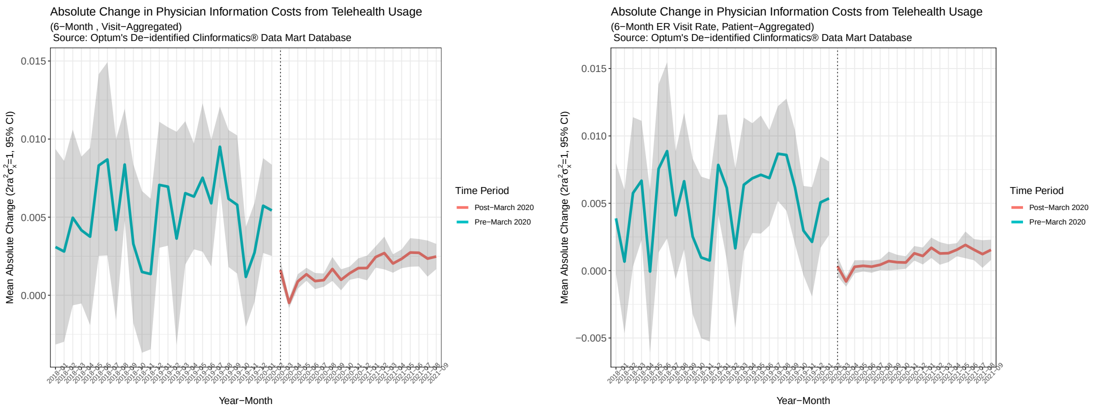


Figure A8: Absolute Change in Information Costs, by ER Visit Rate

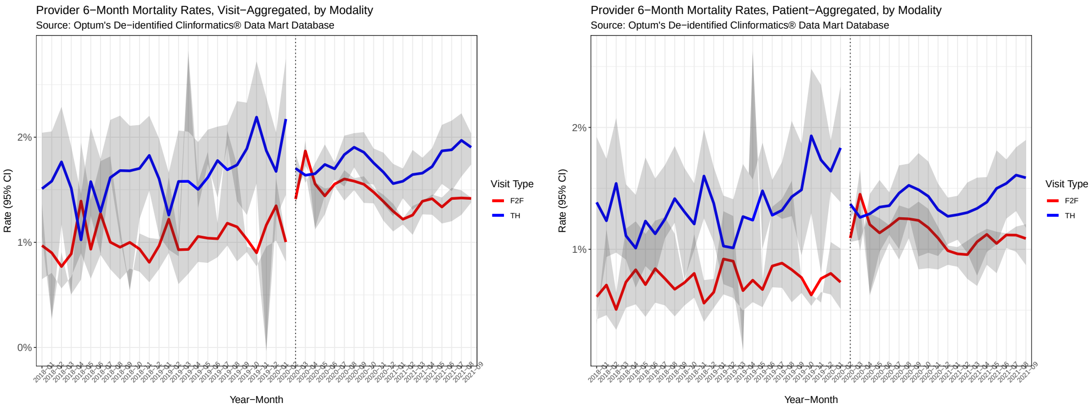


Figure A9: 6-Month Mortality Rates, by Aggregation

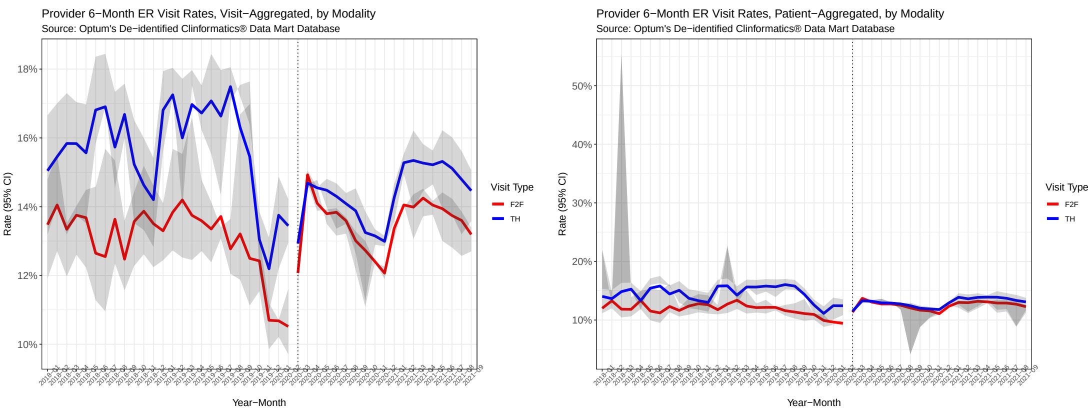


Figure A10: 6-Month ER Visit Rates, by Aggregation

B Robustness Checks

B.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. As an alternative set of specifications to the main results, I improve balance through estimating propensity scores (Rosenbaum and Rubin (1983)) and then reweighting 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

$$\begin{aligned}\mathbb{P}(1^{\text{Telehealth}}_{e,ijt}|\mathbf{X}_{e,ijt}) = F(&\beta_0 + \beta_1 1^{\text{COVID}}_{e,ijt} + \beta_2\text{Age}_{it} + \beta_3\text{CCI}_{it} \\ &+ \gamma_{\text{Race}_i} + \gamma_{\text{Gender}_i} + \gamma_{\text{State}_j} + \gamma_{\text{CPT Code}_e})\end{aligned} \tag{21}$$

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.

Figure B1 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.

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:

$$IPW = \begin{cases} 1/PS & \text{when } 1^{\text{Telehealth}} = 1, \\ 1/(1-PS) & \text{when } 1^{\text{Telehealth}} = 0. \end{cases} \tag{22}$$

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 can handle more 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:

$$OLP = \begin{cases} 1 - PS & \text{when } 1^{\text{Telehealth}} = 1, \\ PS & \text{when } 1^{\text{Telehealth}} = 0. \end{cases} \tag{23}$$

Figure B2 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 we 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.

With both sets of weights constructed, I follow a doubly robust estimation approach (Funk et al. (2011)) where estimation procedures following the empirical framework in Section 4 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.

Figures B3 and B4 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. Table B1 below provides a comparison of post-March 2020 mean average marginal effects for all levels of analysis across unweighted and weighted strategies. These additional steps reinforce the conclusions from the main results, providing a clearer picture of the impact of telehealth usage on severe health outcomes.

Table B1: 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

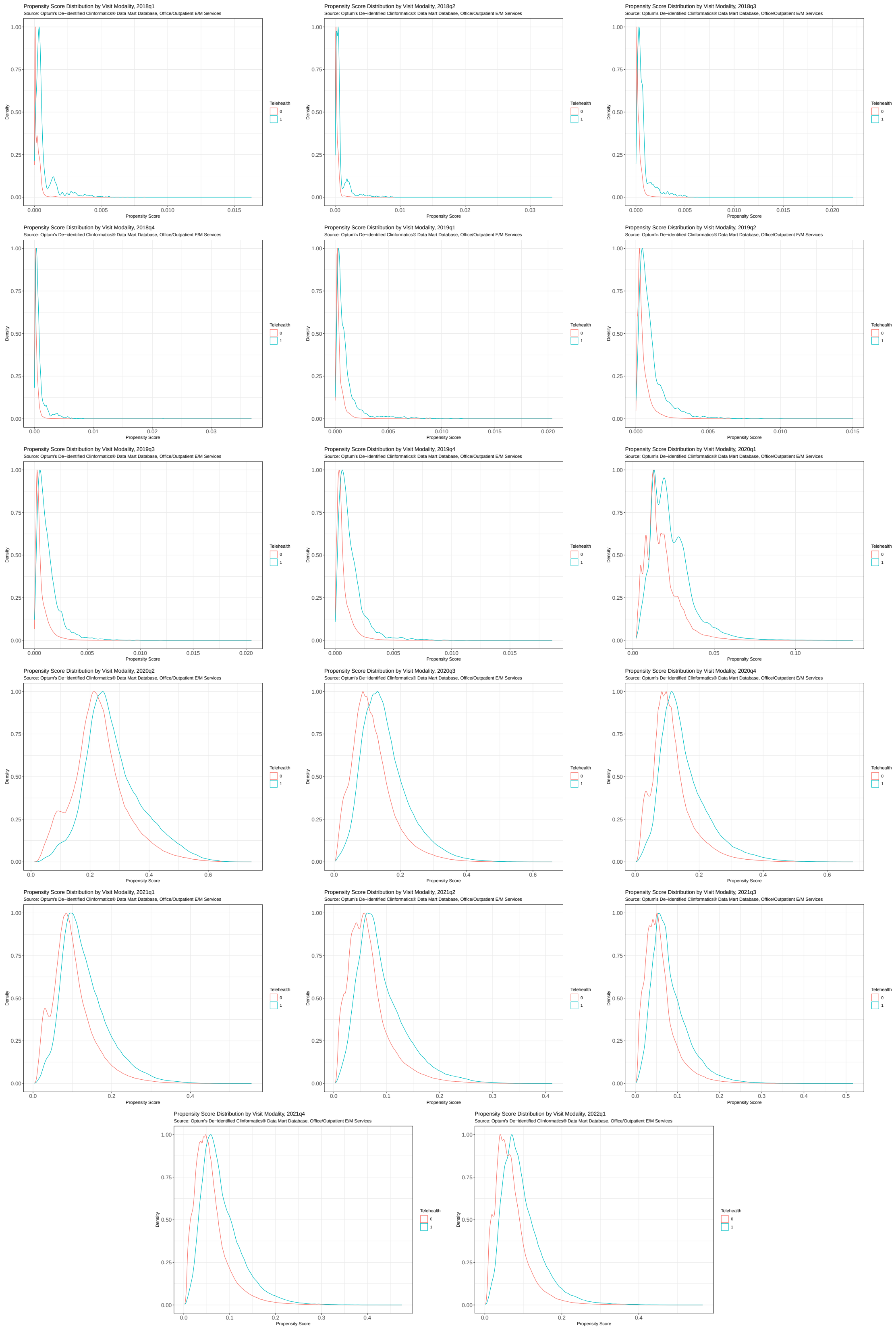


Figure B1: Propensity Score Distribution by Telehealth Usage, 2018q1 to 2022q1

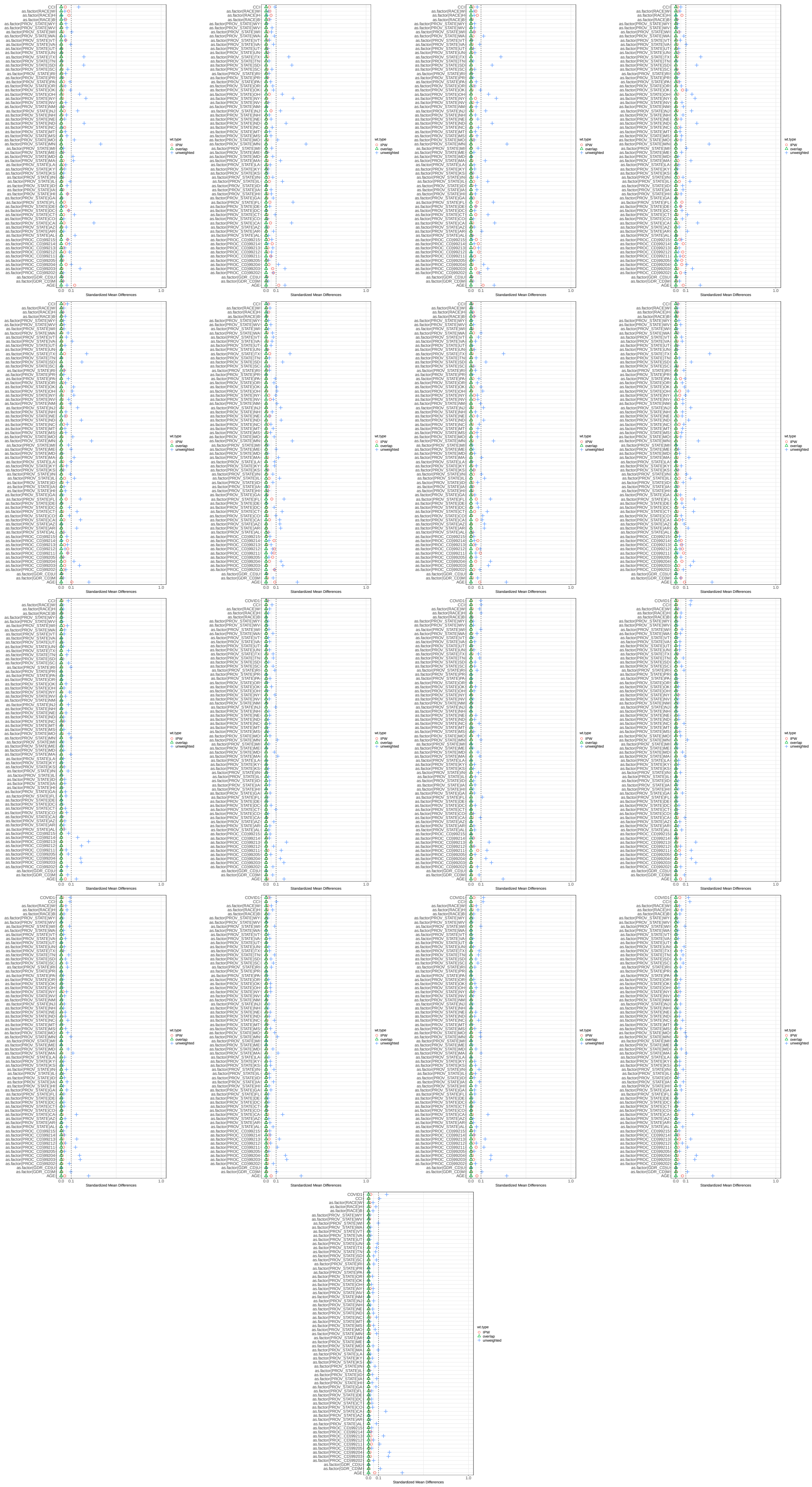


Figure B2: Balance of Covariates, 2018q1 to 2022q1

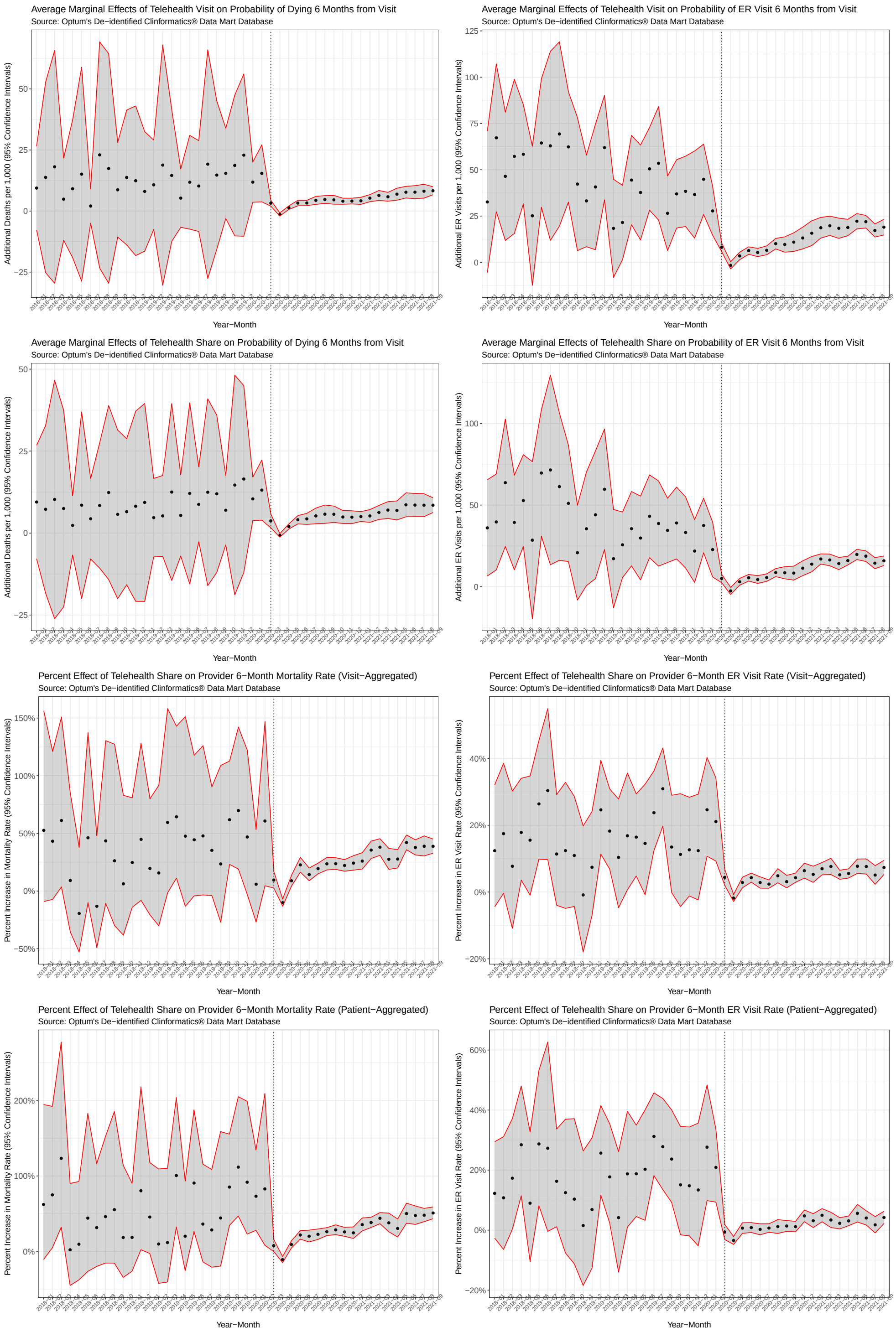


Figure B3: Reduced-Form Estimation Results with IPW

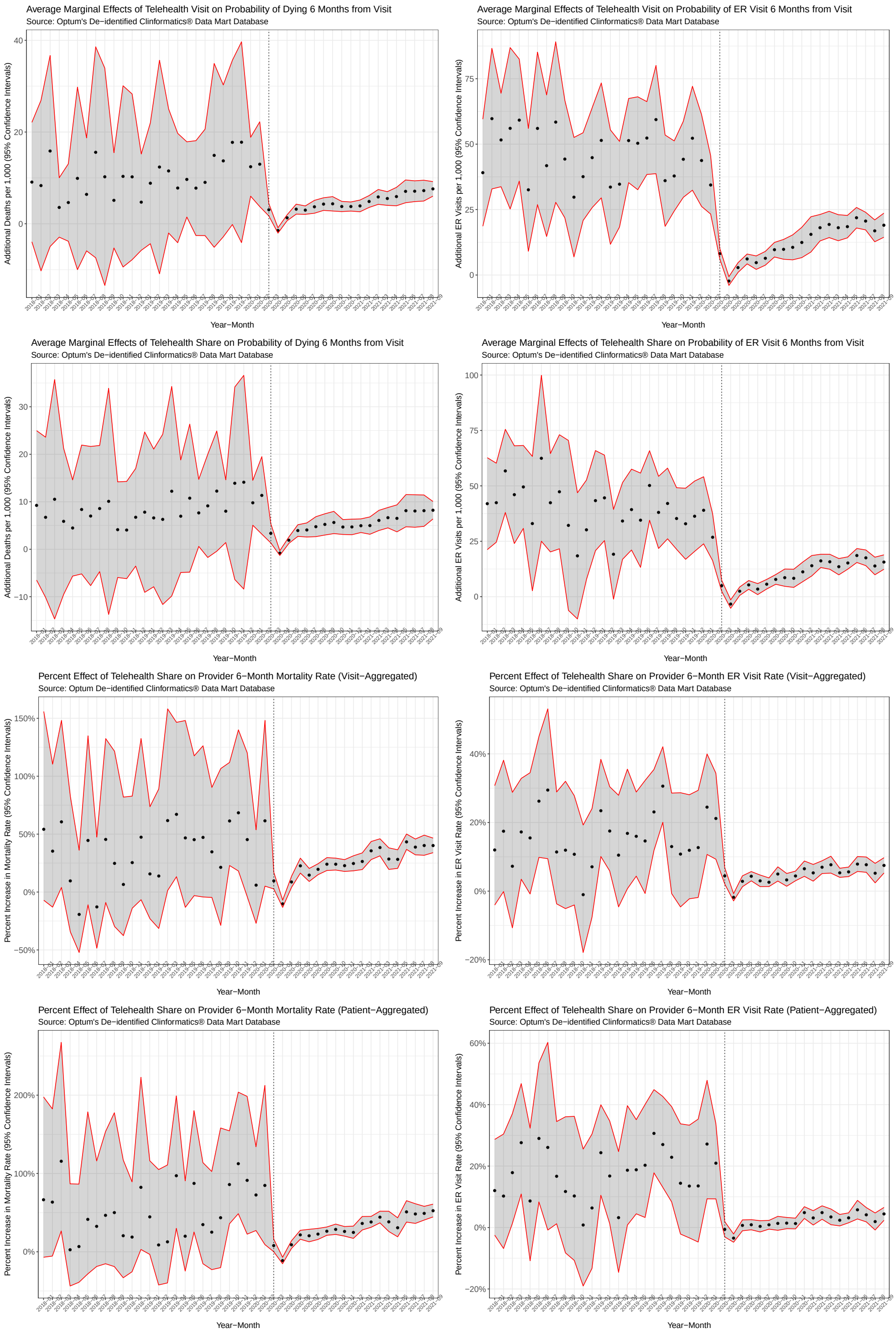


Figure B4: Reduced-Form Estimation Results with OLP

B.2 Sources of Potential Endogeneity

In this section of the appendix, I wish to address additional sources of potential endogeneity regarding telehealth usage. While I cannot ensure that telehealth usage occurred through random assignment, I address a set of potential factors that could could contribute to endogenous assignment. In each case, I present why these factors could be affecting the main results and how I account for them.

B.2.1 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 B5 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.

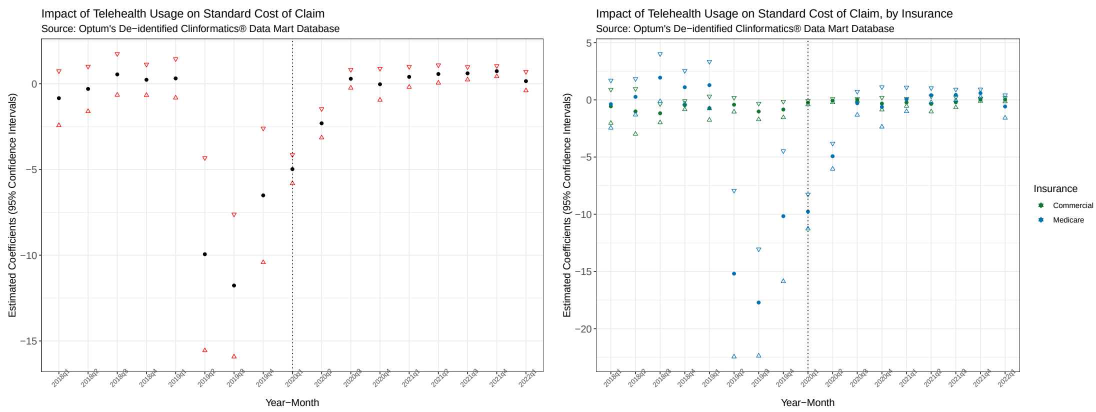


Figure B5: Telehealth and Standard Cost, Overall and by Insurance Type

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 B5 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.

B.2.2 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, but both directions are possible sources of concern.

To account for this, I test whether higher Charlson Comorbidity Index (CCI) scores are associated with telehealth usage at the encounter level. 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. 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 B6 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, suggesting sicker patients were more likely to use telemedicine by appointment. 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.

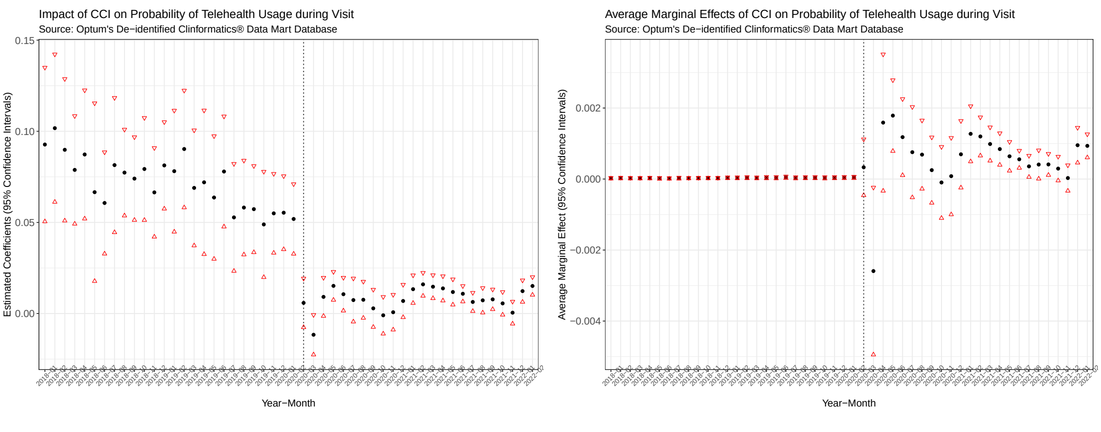


Figure B6: CCI and Telehealth Usage, Impacts and Average Marginal Effects

From this test, I conclude that there is little to suggest telehealth usage is systematically more likely when patients are more sick (or more healthy, either). While I include CCI as a covariate in my empirical analysis to control for underlying health status, I do not consider the patient's underlying health status as a key driver of telehealth usage.

B.2.3 COVID-19 Diagnosis

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

There are many possible ways to account for COVID-19 in this empirical analysis besides the way described above. Alternative methods include using any COVID-19 diagnosis prior to a severe health outcome for a given patient, as well as using a COVID-19 diagnosis associated with the severe health outcome itself. With respect to the best approach for this context, the analysis occurs at the level of the claim or is aggregated from the claim level to the patient-month or provider-month level. It is therefore natural to test in the same fashion if a COVID-19 diagnosis at the same time leads to a severe health outcome within 6 months.

There may be concern that someone without COVID-19 at the time of an E/M service claim actually ends up contracting COVID-19 and experiencing a COVID-caused severe health outcome later on. In the empirical framework, I assume that all patients with a service claim, telehealth or face-to-face, are equally likely to incur an independent shock that could lead to a severe health outcome (e.g., a car accident). In the same way, I assume that all patients with a service claim, COVID-associated or not, are equally likely to incur an independent shock that could lead to a severe health outcome, COVID-related or not. I do not assume that patients with a COVID-associated service claim are as likely to experience a severe health outcome related to that service claim within 6 months as patients without COVID-19 diagnosis codes on their claim.

There could be grounds to question these assumptions on equal likelihood of unrelated shocks. For instance, it could be the case that patients who are seen over telehealth are more likely to stay at home throughout the pandemic, and thus are less likely to die, say, by car accident, than patients who are seen face-to-face and resumed life as normal much more quickly. However, there are many such possible instances of these sorts of changes in lifestyle, including ones that work in the other direction (e.g., lack of socialization, mental health, exercise) which could make telehealth patients more likely to experience a severe health outcome outside of the reason for their service visit. All in all, there is a further complexity in attempting to predict whether patients with telehealth visits or patients with face-to-face visits are more likely to experience unrelated severe health outcomes throughout the duration of the pandemic.

Of course, these lines of reasoning also assume that patients with a telehealth claim always use telehealth and likewise for face-to-face claims, but this is not necessarily the case. Without additional data, it is difficult to characterize risk preferences of patients who have used telehealth versus those who used face-to-face services. Thus, I make the assumption across COVID-19 and non-COVID-19 patients as well as across telehealth and face-to-face patients that there is an equal likelihood of orthogonal shocks that may lead to severe health outcome within the 6 months after a service claim.

Given that we look for COVID-19 diagnoses attached to claims, we may be concerned that effects of telehealth usage are driven by patients who contracted COVID-19. Given the context of the pandemic, it is entirely possible that providers mostly used telemedicine for patients who 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 B7 illustrates this evolution, revealing that the majority of visits with an observed COVID-19 diagnosis are face-to-face rather than telehealth appointments.

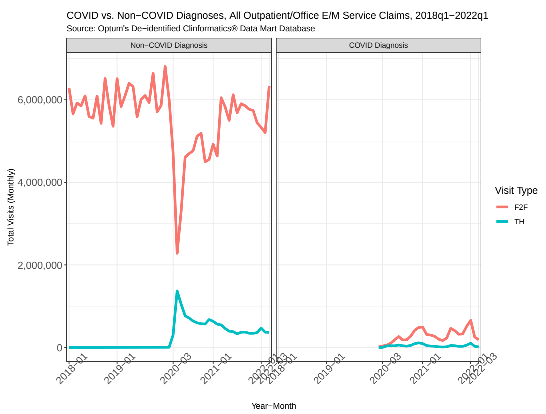


Figure B7: Telehealth vs. Face-to-Face Trends by COVID-19 Diagnosis

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 B8 shows us 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, COVID diagnoses lead to higher likelihood of telehealth usage, conditional on demographic, health status, and visit controls.

Given that 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

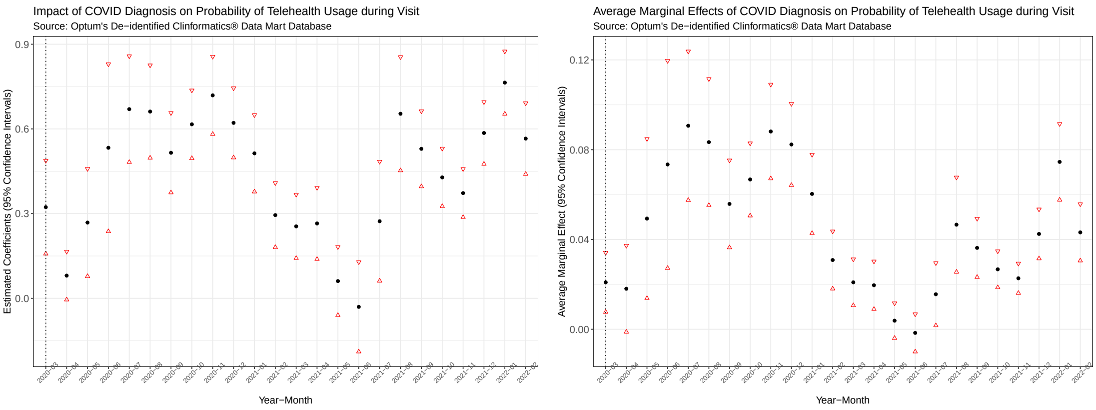


Figure B8: COVID-19 and Telehealth Usage, Impacts and Average Marginal Effects

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.

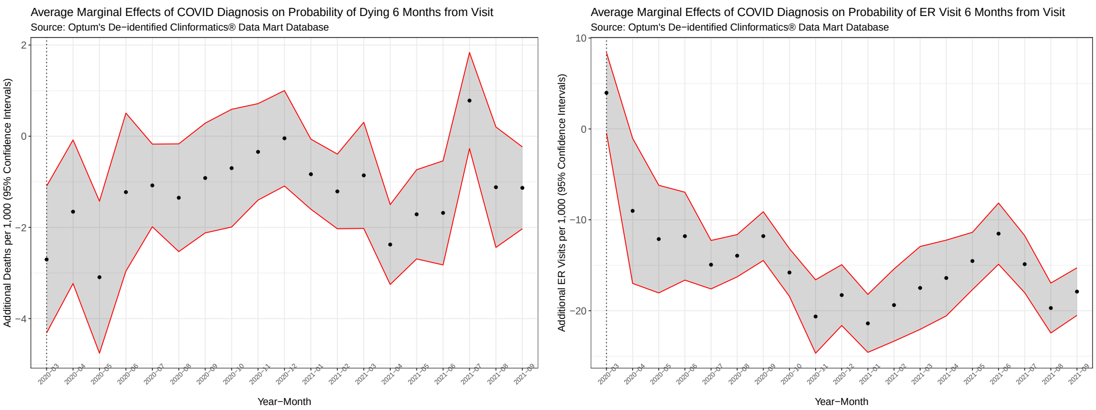


Figure B9: Encounter-Level Reduced-Form Estimation Results, COVID-19

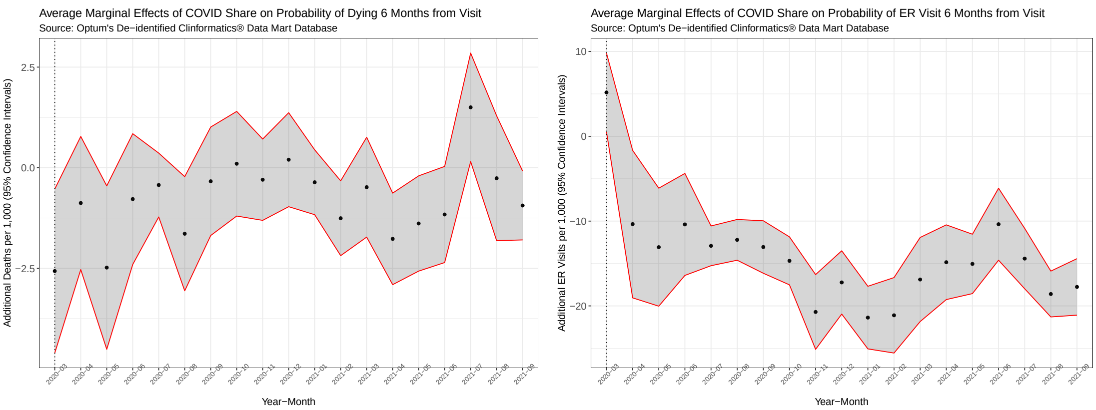


Figure B10: Patient-Level Reduced-Form Estimation Results, COVID-19

Figures B9, B10, and B11 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 the encounter, patient, and provider level, respectively. 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

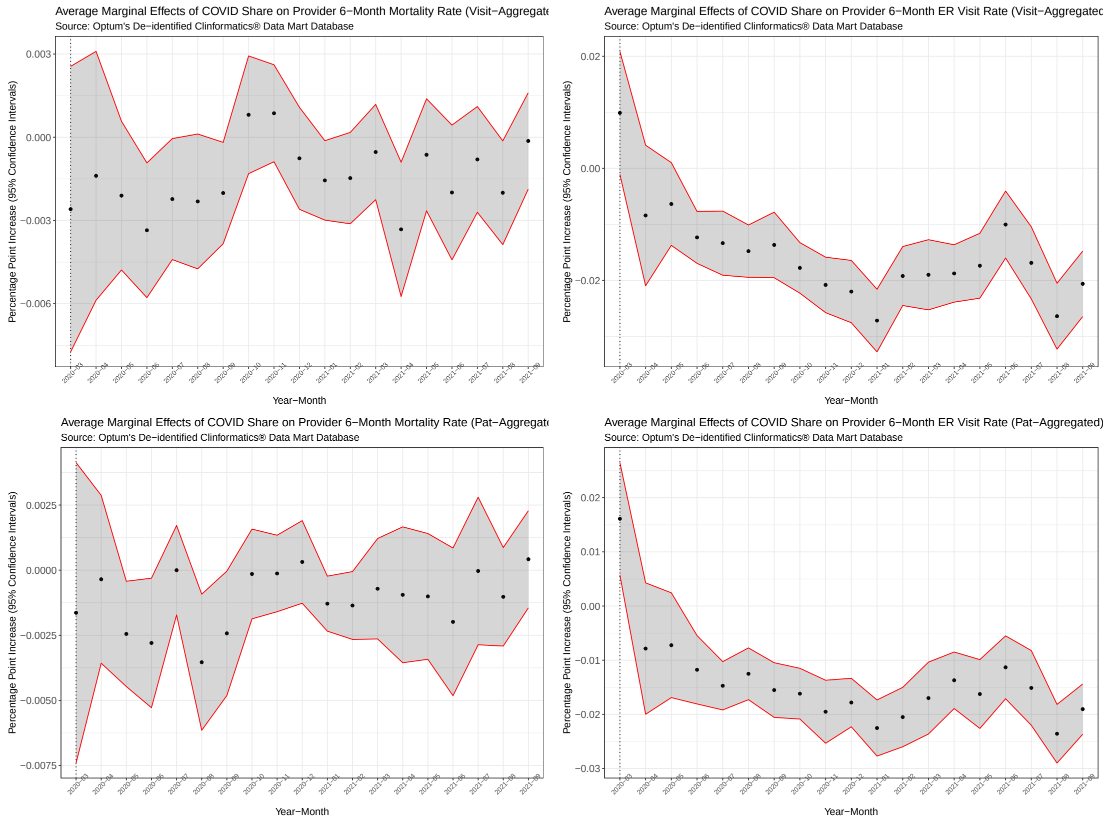


Figure B11: Provider-Level Reduced-Form Estimation Results, COVID-19

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 a severe health outcome upon having COVID-19.

With respect to the main results of this paper, I account for the role that COVID-19 diagnoses play by including an indicator for COVID-19 diagnosis at the time of visit in the reduced-form specifications.

B.3 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.