The Effects of Telemedicine on the Treatment of Mental Illness: Evidence from Changes in Health Plan Benefits[*]

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Abstract

The COVID-19 pandemic resulted in an explosion in demand for telemedicine and with it myriad new, untested telemedicine policies. The effects of these policies are largely unknown, and the shift to telemedicine can have longstanding impacts. We isolate the impact of a policy which reduced cost-sharing for telemedicine services from April-September 2020, estimating changes in telemedicine utilization, the elasticity of demand, and the degree of substitution with in-person services. Additionally, we study the effects of shifting to the virtual environment on mental health treatment decisions, adverse health events, and overall spending. We estimate the elasticity of telemedicine to be -0.21, and that it is used as a near perfect substitute for in-person care, resulting in no net increase in utilization. For those with mental illness, we find that increasing telemedicine use results in more psychotherapy sessions and a reduction in the use of prescription medications. Finally, we show that higher rates of telemedicine use lead to a modest reduction in spending and a higher probability of receiving emergency department care.

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1. INTRODUCTION

It has been estimated that one in five US adults live with a mental health condition, with 4.6% suffering from a serious mental illness, such as schizophrenia, manic depression, or bipolar disorder (NAMI 2020). Mental illness is the top contributor to disease burden in the United States, surpassing cancer and cardiovascular diseases in terms of disability-adjusted life years (Kamal et al., 2017). Individuals suffering from serious mental illness die, on average, ten years earlier than those in the general population, and the mortality associated with mental illness makes up approximately 14.3% of annual global deaths (McGinty et al. 2016; Olfson et al. 2015; Walker, McGee, and Druss 2015). Mental illness has been a particular concern during the COVID-19 pandemic, which saw a dramatic increase in the prevalence of reported rates of psychological distress and triple the rate of reported symptoms of anxiety or depression relative to the prior year (Czeisler et al., 2020; McGinty et al., 2020; Simon et al., 2020). Worryingly, despite the health risks, it is estimated that fewer than half of people living with a mental illness receive any form of treatment (*Mental Illness*, 2019) – an issue that is expected to be exacerbated by the surge in mental health issues attributable to the pandemic (Simon et al., 2020).

Telemedicine, here defined as the use of asynchronous or synchronous audio/audio-video communication to establish a connection between a physically distant patient and provider, has been touted as a promising way to connect patients with scarce access to mental health services to providers (Dorsey & Topol, 2016; *What Is Telepsychiatry?*). Systematic reviews of clinical trials assessing telemedicine have shown that telemental health – the use of telemedicine in treating mental illness – is clinically effective at treating patients will mental illness (Chakrabarti, 2015; Hilty et al., 2013; Totten et al., 2016). Furthermore, telemedicine has been shown to reduce barriers to accessing care, substantially reduce travel time, and save money in travel costs (Hatcher-Martin et al., 2016; Russo et al., 2016). It has also been found that access to telemental health care has been effective at reducing the urban-rural gap in behavioral health specialty care use and in helping those with mental illness maintain contact with their established mental health provider (Huskamp et al., 2018b; McDowell et al., 2021; Patel et al., 2020).

Despite the demonstrated clinical effectiveness, there have historically been significant barriers to the widespread adoption of telemental health, including a restrictive regulatory environment for providers and an unwillingness among payers to reimburse for telemedicine services

(Tuckson et al., 2017). While the technology had been present for decades, telemedicine utilization was virtually non-existent prior to March 2020 (Ashwood et al., 2017; Barnett et al., 2018; Mehrotra et al., 2017). However, the COVID-19 pandemic and the social-distancing policies put into place to slow the spread of the disease resulted in an explosion in demand for telemedicine, accompanied by myriad new, untested telemedicine policies aimed at facilitating its use. Telemedicine utilization accelerated in March 2020, accounting for over a third of all encounters with the healthcare system and nearly half of all mental health encounters in the second quarter of 2020 (Alexander et al., 2020; Patel et al., 2021a, 2021b; Weiner et al., 2021). Our results, which represent data through the end of 2020, indicate that the increase in telemedicine and telemental health use has held steady even after the introduction of several effective COVID-19 vaccines and the relaxation of social distancing policies, suggesting that the elevated level of telemedicine utilization will likely be a permanent fixture of the new healthcare landscape.

The effects of the telemedicine policies enacted during the pandemic are largely unknown, and the shift to virtual care can have unexpected impacts. Understanding the direct effects and potential unintended consequences will be crucial in setting the foundation for telemedicine and mental health policy in the post-pandemic landscape. To that end, this paper has two aims. First, we isolate the effects of one policy designed to encourage the use of telemedicine – reducing patient-side cost-sharing for telemedicine services – and estimate its effects on telemental health utilization and on several outcomes related to the treatment of mental illness. Second, we study how shifting from the in-person setting to the virtual setting affects mental health treatment decisions, the probability of experiencing an adverse health event, and overall spending. We supplement these analyses by exploring heterogeneity of effects across a range of different mental disorders and demographic characteristics.

Disentangling the effects of individual policies is difficult in this environment because of the concurrent policy and behavioral changes induced by the pandemic. We address endogeneity concerns using two identification strategies. To estimate the effects of the cost-sharing waiver on telemental health and overall mental health utilization, we employ a difference-in-differences design, exploiting the sudden introduction of a telemedicine cost-sharing waiver from April – October 2020 which affected employees with employer-sponsored insurance in fully-insured health plans but not employees in self-insured plans. These difference-in-difference analyses show the cost sharing waiver led to a differential increase in the use of telemedicine and a decrease in in-person care for those in fully-insured plans, relative to those in self-insured plans. Next, we use this cost-sharing waiver as an instrument for the share of services received via telemedicine to estimate the causal effects of increased telemedicine use on mental health treatment decisions, the probability of experiencing an adverse health event, and overall spending.

Our study makes three contributions. First, this paper is the first to estimate the elasticity of demand for telemedicine and telemental health since the surge in demand for virtual services. We couch this finding in the broader literature spanning back to the RAND Health Insurance Experiment which relates elasticities to moral hazard (Manning et al., 1987). We use benchmark estimates from this literature to assess the level of risk of overuse and excessive spending resulting from reductions in telemedicine cost-sharing. We conclude that virtual services are relatively inelastic and therefore pose a low risk of moral-hazard-induced overuse. These findings have implications for payers and policymakers in designing and regulating plan benefits to incentivize an optimal use of care.

Second, our paper provides insight into the ability of telemental health to increase access to care for the large share of mentally ill not receiving treatment. While telemental health has long been proposed as a possible way to bridge the access gap in mental health care (Krupinski et al., 2004), its relative rarity prior to the pandemic made it difficult for researchers to empirically estimate its effects on access to care in a generalizable way. With the expansion of telemental health brought about by the pandemic, we are able to estimate the effects it has on increasing access to care now that it has reached scale.

Third, we estimate the causal effects that shifting from the in-person setting to the virtual setting has on a variety of outcomes. While the clinical case for telemedicine has largely been made using randomized-controlled trials (Chakrabarti, 2015; Totten et al., 2016), the real-world effectiveness has not been studied as extensively. Although several studies have explored the effects of telemedicine in real-world settings using observational data, most were conducted prior to the pandemic, making generalizability difficult (Grecu & Sharma, 2019; Harvey et al., 2019a; Neufeld et al., 2016). Additionally, we improve upon prior studies by combining a natural experiment and a rich claims database that allows for the identification of individuals over time and is suited for more nuanced analyses than have been conducted previously. Several other contemporary studies explore the relationship between telemedicine and mental health utilization during the pandemic (Mansour et al., 2020; Nguyen et al., 2021; Ziedan et al., 2020), though to our knowledge only one other study evaluates the causal effect of telemedicine on downstream outcomes (Zeltzer et al., 2021), and ours is the first to estimate these effects for a United States population. Specifically, we study the impact of the shift to telemedicine on mental health treatment decisions (i.e. the use of psychotherapy or psychotropic medications), adverse health events (i.e. inpatient or emergency department admission), and overall spending. Finally, our study uses a novel instrument to address endogeneity concerns which can be employed in other settings to study the effects of increasing telemedicine use on outcomes in a wide range of clinical settings.

The paper proceeds as follows. Section 2 provides background and a literature review on the historical use of telemedicine, the effects of health plan benefit design on utilization, and contemporary work on changes in healthcare delivery during the COVID-19 pandemic. Section 3 lays out our conceptual framework. Section 4 discusses our data and sampling procedures. In Section 5 we detail our identification strategies and statistical analyses. We present our results in Section 6, and end with a discussion of how our results can be interpreted within the context of the emerging literature in Section 7.

2. BACKGROUND

2.1. **Evolution of Telemedicine Policies and Utilization**

For decades, experts have seen the potential of telemedicine to connect people to care, particularly when physical access is limited by geographic barriers in sparsely populated regions of the country (Krupinski et al., 2004). Clinically, the case for telemedicine in treating mental illness is very strong. Systematic reviews of clinical trials assessing the efficacy of telemedicine have shown that it is broadly effective at treating patients with a variety of conditions, including mental illness (Chakrabarti, 2015; Hilty et al., 2013; Totten et al., 2016). From an access perspective, telemedicine has been shown to substantially reduce travel time and potentially save money relative to in-person care. Studies of time and cost-savings have found reductions in travel time on the order of two hours and savings from travel-costs of approximately $30 per visit (Hatcher-Martin et al., 2016; Russo et al., 2016).

While telemedicine has historically made up a small share of all healthcare encounters, it had been growing rapidly prior to the pandemic – particularly in the subfield of telemental health. One study showed an 8-fold increase in overall telemedicine visits from 2010 to 2015 in Minnesota across all payers, and another reported that the number of telemental health visits for rural Medicare beneficiaries with a mental illness increased by a factor of 40 between 2004 and 2014 (Mehrotra et al., 2017b; Yu et al., 2018). Despite the proven efficacy, however, there have historically been several barriers to the widespread adoption of telemedicine, including a restrictive regulatory environment for providers, an unwillingness among payers to reimburse for telemedicine services, and patient hesitancy.

From a policy perspective, telemedicine services were not universally covered or fully reimbursed prior to the pandemic. For example, prior to 2020, Medicare would only reimburse for a telemedicine procedure if a patient was located in a Health Professional Shortage Area or a rural area. Further, telemedicine would not be reimbursed if delivered in the home, and had to be administered in an eligible facility to qualify for reimbursement[1] (*Telehealth Policy 101 - CCHP*, 2021). In many states, private payers were not required to cover telemedicine procedures, or if they voluntarily did it was common to reimburse providers at a lower rate than for equivalent procedures provided in-person (Volk et al., 2021). An additional barrier to using telemedicine has been the Ryan Haight Online Pharmacy Consumer Protection Act of 2008, which made it illegal for providers to prescribe medications online without establishing a patient-provider relationship which requires at least one in-person visit (US Congress 2008; Huskamp et al. 2018). This act, though intended to prevent harm, reduced the usefulness of telemedicine, likely contributing to its underuse prior to 2020.

Some states had taken action prior to 2020 to encourage the use of telemedicine. One of the most widely-adopted policy actions involved mandating private-payer telemedicine coverage parity, which required private insurers to cover telemedicine services if they covered an equivalent in-

[1] There is a complex set of exemptions to these requirements, including for those with substance use disorder or mental illness after 2019. However, generally telemedicine use was narrowly restricted to certain geographies and facilities.

person service. Several studies have explored the effects of telemedicine coverage parity laws. One found that these laws increased primary care utilization, particularly in rural areas, though did not result in a measurable improvement in health outcomes (Grecu & Sharma, 2019). Other studies similarly found that coverage parity laws result in increased utilization of outpatient telemedicine services for both privately-insured and Medicare beneficiaries (Harvey et al., 2019b; Neufeld et al., 2016). These studies provided early evidence that the policy environment has an impact on the way that we use telemedicine.

Since the pandemic, the most restrictive telemedicine regulations have been removed and additional policies to encourage the use of telemedicine were put into place, though many were enacted only for the duration of the public health emergency. Volk and colleagues document changes in the policy environment made between March 2020 and March 2021 (Volk et al., 2021). Some prominent examples include Medicare removing its originating site requirements for patients and allowing the home to be an eligible location to receive telemedicine, several states modifying their laws to require telemedicine coverage or increase telemedicine reimbursement rates paid by private insurers, and the Drug Enforcement Administration relaxing the requirement to establish an in-person relationship prior the online-prescribing. Importantly for our study, some insurers voluntarily adopted policies to facilitate telemedicine use amongst their members, including amending their plan benefit design to temporarily remove patient-side cost-sharing for telemedicine services (Volk et al., 2021). There is a large literature on the effects that plan benefit design has on the way that patients use care, as is discussed in the next section.

2.2. **Plan Benefit Design and Moral Hazard**

Patient-side cost-sharing as a form of managed care has long been advocated for by economists as a valuable contract feature to incentivize optimal healthcare use in the face of moral hazard – a propensity to overconsume medical care when fully-insured due to the negligible marginal cost of care facing the insured[2] (Einav & Finkelstein, 2018; Feldstein, 1973). There is an extensive literature on the effects of cost-sharing on healthcare utilization, spending, and health outcomes.

[2] This specifically refers ex post moral hazard in the context of health insurance, whereas more general definitions of moral hazard involve a predisposition to increased risk when the agent does not bear the cost associated with that risk. In the health economics literature, ex ante moral hazard refers to an agent engaging in riskier behavior prior to the onset of an ailment, and ex post moral hazard refers to using a greater quantity of care than the agent would otherwise consume had they borne the full cost of that care.

The RAND Health Insurance Experiment (HIE) is often considered the 'gold-standard' of evidence that cost-sharing reduces utilization and spending, though does not appear to have an adverse effect on patient health (Manning et al., 1987). Since dissemination of the HIE results, many authors have revisited the topic, reinterpreting the RAND results in light of new developments in the healthcare landscape, evaluating the effects of different types of cost-sharing arrangements, and exploring more nuanced effects in response to critiques of cost-sharing (Aron-Dine et al., 2013, 2015; Baicker et al., 2015; Brot-Goldberg et al., 2017; Bundorf, 2016; Einav et al., 2015; Eisenberg et al., 2017; Rabideau et al., 2021).

The perennial interest in this topic is partly explained by the impact that findings can have on real-world policy. The divergence in the way that we paid for mental health and medical-surgical services from the 1980s through 2008 serves as a telling example. The initial RAND HIE and related work on cost-sharing found that mental health services had a substantially larger elasticity of demand than medical-surgical procedures, implying a higher predisposition to moral hazard (Manning et al., 1989; McGuire, 1986). This finding was used as the basis for insurance plans distinguishing between medical-surgical and mental health procedures, often subjecting mental health services to less generous benefits (e.g. higher cost-sharing obligations, higher out-of-pocket maximums) in efforts to dissuade overuse of care and limit the growth in healthcare spending (Barry et al., 2010). Renewed interest in the topic in ensuing decades found that, with the introduction in provider-side cost-saving innovations in managed care, the effects of patient-side cost-sharing for mental health services had become more closely aligned with the effects on medical-surgical services (Busch & Barry, 2008; Ching-to Albert & McGuire, 1998; Goldman et al., 2006; Goldman et al., 1998). These new findings ultimately resulted in the Mental Health Parity Act of 1996 and the Mental Health Parity and Addiction Equity Act of 2008, which mandated health plan benefit parity between mental health and medical-surgical procedures (Barry et al., 2010). The interplay between patient-side cost-sharing, changes in utilization, and policy action highlights the importance of research on this topic.

We conclude this section with important background on a subtle difference in how different firms that offer employer-sponsored insurance (ESI) handle health plan benefits. ESI makes up a majority of health coverage in the US (*Health Insurance Coverage of the Total Population*, 2019), though there is heterogeneity in how firms offer this care. Firms that purchase health plans from a third-party insurance company and offer these plans to their employees are known as fully-insured firms. This is in contrast to self-insured firms, which are firms that opt to insure their employees against medical expenses themselves, directly reimbursing providers for costs incurred by their employees, and contracting with insurance companies only to negotiate with providers and process claims, but not bear risk (*2020 Employer Health Benefits Survey*, 2020). Since self-insured firms offer health benefits directly, they control the structure of those benefits (e.g. the amount of patient cost-sharing, selecting which services to cover), in contrast to plans offered by fully-insured firms, which are products offered by third-party insurance companies, where it is the insurance company who decides on the benefit structure of the plan. There are substantial numbers of each type of firm, with self-insured firms representing 67% of employees with ESI, and fully-insured firms making up 33% (*2020 Employer Health Benefits Survey*, 2020). Differential changes in telemedicine cost-sharing between plans offered by fully-insured and self-insured firms in response to the COVID-19 pandemic will serve as the primary source of identifying variation in this paper, as discussed in Section 4.

2.3. Healthcare Delivery During COVID-19

The COVID-19 pandemic and the barrage of policies passed in response to it upended many aspects of daily living in the United States. Schools and universities closed campuses and sent their students to home isolation, state and local authorities enacted shelter-in-place policies and curfews to prevent interpersonal contact, non-essential businesses had their doors shuttered to dissuade superfluous gatherings, and large social gatherings were often prohibited (Amuedo-Dorantes et al., 2020; “Canceled Events Because of Coronavirus List - The New York Times,” 2021; *State Action on Coronavirus (COVID-19)*, n.d.; Cantor et al., 2020; Gupta et al., 2020; Matrajt & Leung, 2020). The pandemic also evoked a behavioral response whereby individuals voluntarily engaged in social-distancing (i.e. maintaining physical distance between themselves and others), self-quarantining at home when experiencing symptoms or having been in high-infection-risk situations, and shifting to contactless services where possible[3] (Gupta et al., 2020; Yan et al., 2021).

[3] These policies and individual behaviors are far from exhaustive and were selected to demonstrate both the scale of the response to the pandemic as well as highlight actions that would reduce mobility and increase isolation, which is of particular relevance to the topic at hand.

In an attempt to triage care and reserve healthcare resources for the surge of COVID-19 patients, The Center for Medicare and Medicaid Services, the Veterans Administration, and state and local authorities enacted temporary pauses for elective procedures at various times during the pandemic (Mensik, 2020; Tran et al., 2021). The combined effect of these policies and voluntary behavioral changes was a 60% decrease in in-person office visits and a 30% reduction in hospital admissions relative to prior years (Cox et al., 2021; Heist et al., 2021; Mehrotra et al., 2020, 2021). This massive disruption to healthcare delivery necessitated a rapid shift to treatment modalities which were both compliant with official policy and accommodating to the population's sensibilities regarding the risk of interpersonal contact. Telemedicine naturally arose as an obvious solution, with the number of telemedicine services increasing by orders of magnitude from February to April 2020 (Alexander et al., 2020; Cantor, McBain, Kofner, et al., 2021; Cantor, McBain, Pera, et al., 2021; Lau et al., 2020; Mansour et al., 2020; Patel et al., 2021a, 2021b; Weiner et al., 2021).

The fundamental challenge to studying the effects of these policies and the shift to telemedicine is that they were passed in response to the pandemic and are temporally entangled in a way that renders many econometric tools difficult to use. Nevertheless, several researchers have begun the measured process of isolating the causal effects of individual policies which spurred the use of telemedicine, as well as on the effects of telemedicine use on more distal outcomes. Two papers examined the effects of elective hospitalization closures and shelter-in-place policies on the reduction of non-COVID-19 related healthcare services using variation in the timing of these policies between regions, finding significant results of foregone or delayed care (Cantor et al., 2020; Ziedan et al., 2020). Another study examined how the changing demand for telemedicine and in-person care resulted in physician adoption of telemedicine, again using variation in the timing of shelter-in-place orders to identify an effect (Cantor & Whaley, 2021).

Most similar to our study, Zeltzer et al. (2021) estimated the impact of increased access to telemedicine utilization on spending per episode, adverse health events, and patterns of treatment (e.g. the use of prescription medications). They found that increased access to telemedicine resulted in a slight increase in total utilization and a decrease in the cost per episode of care, leading to an overall reduction in spending. They also found modest decreases in referrals, an increase in follow-ups, and fewer prescription fills. Finally, they found no evidence of changes in emergency department use. While there are several similarities between this analysis and our own, their study differs from ours in several key ways. First, Zeltzer et al. use data from Israel during and after the Israeli lockdown, which may not generalize to the US population that we use in our study. Second, our sources of identifying variation differ, with Zeltzer et al. relying on the exogeneity of providers' differential propensities to adopt telemedicine to identify their effects, whereas we make use of a plausibly exogenous change in health plan benefit design involving patient cost-sharing. Finally, their study mainly examines the primary care setting, whereas our study focuses on the mental health setting, which allows us to explore the effects on those with mental illness in more detail.

3. CONCEPTUAL FRAMEWORK

There are several ways that applying a cost-sharing waiver for telemedicine can affect utilization decisions, overall spending, and the probability of experiencing an adverse health outcome. We adopt a stylized version of the health production function from the demand for health owing to Grossman (1972) to explain the underlying relationships which lead to our outcomes:

$$H_t = h\left(H_{t-1}, \delta, \omega\big(\Lambda(\mathbf{1}[\mathrm{v}]), d(\mathbf{1}[v])\big), Q\left(F(p^f, p^v), V(p^f, p^v)\right)\ \right) \tag{1}$$

$H_t = Health\ in\ time\ t$

$H_{t-1} = Health\ stock\ in\ the\ prior\ period$

$\delta =\ the\ rate\ of\ health\ stock\ depreciation$

$\omega =\ a\ measure\ of\ the\ effectivness\ of\ care\ per\ unit$

$Q\ =\ a\ measure\ of\ the\ quantity\ of\ care$

In this model, the first three defined terms follow the standard interpretation from Grossman (1972), with H_t being the stock of patient health at time t, which is itself a function of the stock of health in the prior time period and a natural rate of health depreciation. In addition, health stock is dependent on a set of inputs into health production. The inputs of interest are the quantity of medical care received and the effectiveness of that care per unit. The quantity of care term is a function of the total number of face-to-face services, F, and virtual services, V, both of which are functions of the out-of-pocket price (i.e. cost-sharing obligation) of each type of visit, $\{p^f, p^v\}$. The effectiveness per unit of care term is a function of treatment decisions and provider characteristics, $d(\ )\ and\ \Lambda()$. Provider characteristics are a function of whether or not care was delivered in the virtual setting, as different types of providers may be more or less likely to offer virtual services, resulting in different provider characteristics between the two settings. Similarly, treatment decisions are also a function whether or not the care was delivered in the virtual setting. The rationale for this is that the care received in the virtual setting may be different than the care received in-person, either because of characteristics of the modality itself. For example, patients may be more comfortable engaging in psychotherapy from the comfort of their own home compared to in an office (or less likely if they feel they do not have adequate privacy at home). In this analysis, we focus on the treatment decision between the use of psychotherapy and psychotropic medication for the treatment of mental illness.

There is a large clinical literature on the efficacy of using psychotherapy, pharmacotherapy, or both to treat various disorders in a variety of settings. The results have been mixed, with many best-practice guidelines recommending a combination of the two for the majority of mental health disorders (*Clinical Practice Guideline for the Treatment of Depression Across Three Age Cohorts*, 2019; Cuijpers et al., 2013; Kamenov et al., 2017; Keepers et al., 2020; Locke et al., 2015; Pliszka, 2007; Weir, 2019). However, in practice, the decision of which treatment to use may be influenced by several non-clinical factors, including the type of provider. There are several different types of mental health providers with different practice patterns and scopes of treatment authority, including psychiatrists, psychologists, licensed social workers, and patients' primary care provider (Olfson et al., 2014; *American Psychological Association*, 2017). Further, online prescribing had been regulated prior to the pandemic, which may have resulted in different treatment styles emerging for those habituated to delivering telemental health before the pandemic, or an innate hesitancy for recent adopters of telemedicine to prescribe to patients without an established relationship (*Implementation of the Ryan Haight Online Pharmacy Consumer Protection Act of 2008*, 2020). We focus on how the shift to virtual care may have impacted a patient's use of psychotropic medications and psychotherapy in the treatment of their condition.

Returning to the health production function, the most obvious way that cost sharing enters into our conceptual framework is through its effect on the quantity of care received. Since the waiver lowers the marginal cost of virtual care, p^v, telemedicine utilization should increase by the law of demand (Marshall, 1892). However, the effects on overall (face to face + telemedicine) mental health utilization are more ambiguous. If telemental health is a complement to in-person mental health treatment we might expect an increase in in-person use and therefore a net increase in mental health services. On the other hand, the two may be substitutes, where an increase in one results in the decrease of the other, with ambiguous effects on overall utilization. Several studies have examined the effects of cost-sharing on substitution of care modalities in the health care system. One such study explored the effects of decreased cost-sharing through the use of "copay coupons" for certain drugs on the utilization of those drugs, finding a substantial increase in sales of drugs with coupons coming entirely from substitution from bioequivalents that did not offer a coupon (Dafny et al., 2017). Other studies have found that exogenous increases in pharmaceutical cost-sharing resulted in less drug use which was offset by substitution into more inpatient and outpatient care (Chandra et al., 2010; Gaynor et al., 2007). Further, we define:

$$ED = g(H_t)\ ; \qquad g'(H_t) < 0 \tag{2}$$

$$Inpatient = \phi(H_t)\ ; \qquad \phi'(H_t) < 0 \tag{3}$$

$$Cost = \rho(P(s), Q) \tag{4}$$

Where ED is defined as the probability of having an emergency department encounter, $Inpatient$ is the probability of having an inpatient admission, and $Cost$ is the total expenditure on healthcare services in a time period (combined health plan spending and patient out-of-pocket spending). Both emergency department and inpatient admissions are regarded as being determined by health status at time t, where the probability of each is a decreasing function of H_t. Costs are determined as a function of the quantity of services and the average price per service, $P(s)$, which is a convex combination of the average cost of a telemedicine and in-person service (which we assume are exogenous), weighted by the share of telemedicine services, s.

There are also reasons to think there may be substantial heterogeneity of effects across various subpopulations. For example, while telemental health has shown to be effective at treating a wide range of mental health and substance use disorders, it has been found that those with serious mental illness have historically been much more likely to use these services, indicating that any effects should be exacerbated for this important population (*Telehealth for the Treatment of Serious Mental Illness and Substance Use Disorders*, 2021). Additionally, we may expect that groups that were disproportionately impacted by the pandemic would take advantage of the increased access to telemedicine moreso than others. This includes the elderly, who were particularly vulnerable to COVID-19, as well as those in dense, urban areas who were at highest risk for contracting the disease. Low-income individuals may also be especially responsive to the price changes induced by the waiver. While we do not have data on income or urbanicity, we proxy these using race given the strong associations between these demographic characteristics, noting the black Americans are more likely to live in urban, low-income neighborhoods, and therefore could be large beneficiaries of the reduced prices for using telemedicine (Firebaugh & Acciai, 2016). Because of the strong possibility of heterogeneity across mental illnesses and subpopulations, we stratify our main results by disorder, and present additional results decomposed by age and race in Section 6.4.

4. DATA AND SAMPLE

Our study uses insurance claims data from a nationwide sample of individuals aged 5-64 in the United States with employer-sponsored health insurance. The data is sourced from OptumLabs® Data Warehouse (OLDW) from 2016 through the end of 2020. OLDW is database with broad national coverage and is comprised of de-identified inpatient, outpatient, and pharmacy administrative claims, as well as insurance enrollment and plan benefit information for millions of individuals in the United States. In addition to claims from health plans offered by a health insurance company (i.e. claims from employees in fully-insured firms), The OLDW data also contains Administrative-Services Only (ASO) claims from many self-insured firms. These are firms in which the individual employer acts as the primary payer for their employees, and a health insurance company provides administrative support in processing and documenting their claims. The difference between fully-insured and self-insured plans was discussed in Section 2.2. The inclusion of claims from both fully-insured and self-insured firms will be important for our empirical strategy, as discussed in Section 5. In addition, the data also contains information on patient demographics, diagnosis codes, procedure codes, place of service, dates of service, provider type, a claim paid amount, and claim paid amounts for the deductible, coinsurance, and copay.

Our sample consists of individuals who are continuously enrolled in employer-sponsored health insurance for the entire study period (2016-2020) to mitigate the threat that differential unemployment or job switching may bias our results. While our main analytic time-period is January 2018 – October 2020, we use the longer time-period to create more comprehensive clinical histories for individuals, including identifying the presence of relatively rare mental illnesses. We test the sensitivity of this continuous-enrollment period by re-estimating our results while shortening this time horizon. We further limit our sample based on firm and individual characteristics. For firm selection, we only include employees in large firms with an average of 200 or more employees in a given month. We do this because our main comparison will be between employees in self-insured and fully-insured firms, and self-insured firms tend to be large relative to fully-insured firms (an average of 1,077 employees compared to 48 employees in our sample) and there is reason to believe that there are fundamental differences in insurance coverage and utilization between employees in large and small firms (*2020 Employer Health Benefits Survey*, 2020; Long et al., 2016) In addition, small firms are subject to different rules and treatment as established in the Affordable Care Act, hindering direct comparisons (*Small and Large Business Health Insurance: State & Federal Roles*, 2018). Further, we exclude 13% of firms that switch between being fully-insured and self-insured during our study period, as this distinction forms the basis of our identification strategy as described below. Finally, we exclude 10% of self-insured firms that we identified as having waived cost-sharing for telemedicine services for their employees, as this action could be viewed as a violation of the stable unit treatment value assumptions imposed by the potential outcomes framework and described in our identification strategy in Section 5. After these firm level exclusions, we were left with 74% of our original sample of employees (685,216 unique individuals and 41,112,960 person-months).

For enrollee selection, we further limited our sample to those who remained in the same firm and state throughout the study period (2016-2020). Finally, we limited our sample to those who lived in one of the 36 states that had already adopted private-payer telemedicine coverage parity mandates prior to March 2016 (*State Telehealth Laws and Reimbursement Policies*, 2020). The rationale for this is that these states adopted telemedicine coverage mandates prior to COVID-19 and therefore did not self-select into mandating telemedicine coverage in response to the pandemic, meaning that any changes in telemedicine use cannot be attributed to changes in telemedicine coverage (i.e. whether insurance reimbursed for telemedicine or not). Our final sample consisted of 486,000 unique enrollees, each enrolled for 60 months for a total sample size of 29,160,000 person-months (January 2016-December 2020) with our main analytic sample (spanning January 2018 – October 2020) being comprised of 16,038,000 person-months.

The main measure in this study is the count of monthly telemental health services per person. A telemental health service is defined at the claim level and is identified as a claim with at least one diagnosis code on the claim indicating a mental illness, and additional information on the claim indicating that the service was performed via asynchronous, synchronous audio-only, or synchronous audio-visual communication at a distance. Services for the treatment of mental illness were identified using a combination of International Classification of Disease diagnosis codes (ICD-10), Current Procedural Terminology 4 (CPT-4) codes indicating psychotherapy, or a provider specialty code indicating treatment from a psychiatrist, clinical psychologist, or licensed social worker, in accordance with existing literature (Azrin et al., 2007; Goldman et al., 2006; Kennedy-Hendricks et al., 2018). Services being provided via telemedicine were defined based on values of an appropriate CPT-4 code, procedure modifier code, or the place of service code (Rae et al., 2020; Weiner et al., 2021). For a full list of codes that identify claims as those for mental illness and those delivered via telemedicine, see Appendix Table A1. This claim-level measure was then aggregated to the person-month level based on the date of service present on the claim to create a count of telemental health services.

We also create outcomes for in-person mental health services using a similar methodology (but with the absence of an indicator for telemedicine), and an outcome for total psychotherapy services received based on an identifying CPT-4 code for psychotherapy (see Appendix Table A1 for the list of psychotherapy codes). In addition, we created several outcomes to capture spending. The first is the out-of-pocket cost for telemedicine services. This outcome is defined as the sum of the deductible, copay, and co-insurance fields on a claim that has been identified as being delivered via telemedicine (and missing otherwise). We also calculate monthly spending measures for telemedicine, mental health, and overall spending by summing the *amount paid* field on each service-appropriate claim and aggregating to the person-month level. For these spending measures, enrollees who had coverage but no claims in a given month are assigned a value of $0 in monthly spending in that month, as is common in the literature when calculating spending with claims data (Rabideau et al., 2021). Our independent variable for the main cost-sharing analysis was a binary indicator representing being in a fully-insured firm from April – October 2020, denoting enrollees who received the telemedicine cost-sharing waiver during the months when it was active.

Table 1 compares summary statistics for those in fully-insured and self-insured firms. Observable characteristics seem generally well-balanced between two groups. However, there are some notable differences. Those in fully-insured firms are more likely to be black (15.2% vs 8.1%) and less likely to be white (58.7% vs 66.2%). There are also geographic differences between the two groups, with those located in the South Atlantic making up a larger share of the fully-insured group (33.8% vs 12.6%). While these differences may make us question the comparability of the two groups, the rich panel structure of our data allows us to use an individual-level fixed effects estimator, which should mitigate the threats from any unobservable, time-invariant confounders. Also of note is that those in fully-insured firms are slightly less likely to receive any mental health service in a given month (4.7% vs 5.1%), which will help frame our results in Section 6.

5. METHODS

5.1. Effects of Cost-Sharing on Utilization

The first part of our analysis seeks to identify the average treatment effect of waiving cost-sharing for telemedicine procedures on the use of telemental health and other utilization measures. However, this is complicated by the fact that the cost sharing waiver coincided with the onset of the COVID-19 pandemic and various social-distancing policies which generated massive demand for telemedicine independently of the reduction in cost-sharing obligations. To isolate the effect of the cost-sharing waiver specifically, we use a difference-in-differences (DD) design, estimating the differential change in telemental health utilization among those who received the cost-sharing waiver relative to those who did not. We exploit the fact that health plans offered to those in fully-insured firms temporarily waived pre-negotiated cost-sharing rates for telemedicine for in-network providers from April – October 2020. However, this waiver did not affect plans for those in self-insured firms, as can be seen in Figure 1. Thus, we use enrollees in fully-insured firms as our treatment group and those in self-insured plans as our counterfactual for how the fully-insured enrollees would have behaved had cost-sharing not been waived. The econometric model is as follows:

$$Y_{ipt} = \alpha_0 + \alpha_1(FullyInsured_p\ X\ Post_t) + \theta_i + \lambda_t + \epsilon_{ipt} \tag{5}$$

Where Y_{ipt} is an outcome for individual i in plan p at time t, $FullyInsured_p\ X\ Post_t$ is an indicator variable for being in a fully-insured plan following the implementation of the cost-sharing waiver, $\theta_i\ and\ \lambda_t$ are individual and year-month fixed effects, respectively, and ϵ_{ipt} is an error term. Since the sample was selected such that enrollees are present in the same firm for the entire study-period and the firms in our sample are either always fully or self-insured, the individual fixed effects identify assignment to the treatment group. The causal parameter of interest is α_1, which represents the effect removing cost-sharing for telemedicine procedures on the outcome of interest. Robust standard errors are clustered at the plan level to account for heteroskedasticity and autocorrelation between individuals in the same plan.

The use of telemental health increased by orders of magnitude after March 2020, as can be seen in Figure 2. Due to the extreme scaling of the dependent variable for both those in the treated and control groups in the post-period, the use of a traditional DD design is inappropriate to identify causal effects, as the scale differences effectively reduces the DD to an ex-post difference in means.[4] To address this, we propose a log-linear difference-in-differences derived from an underlying multiplicative model of the use of telemental health (i.e. measuring a proportional change rather than a level change). We specify a Poisson exponential model:

$$\mu = E[y|x] = \exp(\mathrm{X}\beta)\,\eta \tag{6}$$

$$\ln\left(E[y_{ipt}|\ x_{ipt}]\right) = \beta_0 + \beta_1(FullyInsured_p\ X\ Post_t) + \theta_i + \lambda_t + \xi_{ipt} \tag{7}$$

We estimate this model using a Fixed-Effect Poisson Pseudo-Maximum Likelihood (FEPPML) estimator as suggested in the literature and applied in similar settings with healthcare count data (Gaynor et al., 2007; Silva & Tenreyro, 2006). This estimator has the advantage of being consistent even in the presence of most types of model misspecification, including the violation of the Poisson mean-variance equivalence assumption, the assumption that the dependent variable must follow a Poisson distribution, and excessive values of 0 (Gourieroux et al., 1984; Santos Silva & Tenreyro, 2011; Silva & Tenreyro, 2006; Wooldridge, 1999; Zou, 2004).

[4]Note, for instance, that $(z_1 - z_2) - (w_1 - w_2) \cong (z_1 - z_2)\ for\ \{z_1, z_2\} \gg \{w_1, w_2\}$, where the z values represent the difference between treatment and comparison groups in the post-period, and the w values represent the difference in the pre-period.

Our identification strategy implies that the causal effect of the cost-sharing waiver is captured by the coefficient on the interaction of indicators for being in a fully-insured firm during the post-period (Angrist & Pischke, 2009), however the interpretations of interaction terms in non-linear models are not always intuitive and often differ from the linear setting (Ai & Norton, 2003; Karaca-Mandic et al., 2012). In our proposed multiplicative model, the interaction term represents the logarithm of the ratio of the incidence-rate-ratios of the expectation of the counts of telemental health utilization (Ciani & Fisher, 2019):

$$\exp(\beta_1) = \frac{E[y_{it}|fullins_f = 1, post_t = 1]}{E[y_{it}|fullins_f = 0, post_t = 1]} \Big/ \frac{E[y_{it}|fullins_f = 1, post_t = 0]}{E[y_{it}|fullins_f = 0, post_t = 0]} \tag{8}$$

That is, the exponentiation of β_1 is the ratio of the ratio of the counts between treatment and control groups in the post-period and the ratio of the counts between treatment and control groups in the pre-period.[5] Similar to the log-linear specification which applies a logarithmic transformation to the dependent variable before estimating with ordinary least-squares, the interpretation of the coefficient in this case is approximately a percentage change (Wooldridge, 2010). The main advantage of using the FEPPML estimator over the log-transformed ordinary least-squares estimator is that the FEPPML can tolerate values of 0 as inputs, whereas the log-transformed model cannot since $\ln(0)$ is undefined (Santos Silva & Tenreyro, 2011; Silva & Tenreyro, 2006), and ad-hoc work-arounds such as taking the log of the dependent variable plus some constant (e.g. log(y + 1)) has been shown to introduce potentially problematic levels of bias (Campbell & Mau, 2021).

The key identifying assumption of a difference-in-differences design is that pre-to-post change in the control group is identical to what the pre-to-post change would have been in the treatment group had they not received treatment (known as the parallel trends assumption). While this assumption is untestable, researchers often verify its plausibility by observing whether the pre-

[5] For example: if the ratio of E[counts] in the post period is $\frac{6}{5}$ and in the pre-period it was $\frac{9}{10}$ then the ratio of these ratios would be $\frac{1.2}{0.9} = 1.33$, indicating a 33% increase in the expected counts for those in the treatment group in the post-period relative to what they would have been had the treatment group scaled proportionally to the control group.

period trends in the dependent variable for the treatment and control groups are parallel, which we present visually compelling evidence for in Figure 1 and Figure 2.

5.2. Effects of Telemedicine on Treatment Decisions, Adverse Events, and Spending

We are also interested in the causal effects of shifting to telemedicine use on spending, adverse health events (e.g. emergency department and inpatient admissions), and mental health treatment decisions regarding the use of psychotherapy and psychotropic medication. Measuring medication use in claims data presents additional challenges since it is not known when the patient is prescribed the medication or when they take it, and because different volumes could be prescribed to patients on different medications. We use a days-supplied variable to address many of these issues, where the days-supplied represents the number of days that a medication should be used to treat a patient, which we begin counting from the date that the prescription was filled (which is not necessarily the same date that it was prescribed, which we do not observe). There are limits on the maximum days supplied that can be dispensed at a given time, with the least-restrictive states limiting this to a maximum of 90 days (Taitel et al., 2012). In keeping with this 90-day maximum, we adjust the unit of observation in our study to the person-quarter level. Conveniently, the effective dates of the telemedicine cost-sharing (April 2020 – September 2020) waiver perfectly coincide with standard definitions of calendar-year quarters (i.e. April – June is Q2, July – September is Q3).

For this analysis, we are no longer interested in the effect of the cost-sharing waiver directly, but rather the effect of shifting care modalities from in-person care to telemedicine. To capture this, we define our independent variable of interest as the share of procedures received via telemedicine in a given quarter.

$$ShareTele = \frac{V(p^f, p^v)}{V(p^f, p^v) + F(p^f, p^v)} \tag{9}$$

Where $V(p^f, p^v)$and $F(p^f, p^v)$ represent the person-quarter quantities of virtual and face-to-face services, as defined in Section 3. If no services are received in a quarter, the measure in undefined. If this occurs, we impute the average share of telemedicine for the funding-type-quarter is imputed (i.e. if the enrollee is in a fully-insured (self-insured) plan, the average share for those in fully-insured (self-insured) plans in the same quarter is imputed). Sensitivity analyses are performed which either omit observations where no services are received (32% of sample) or where 0 is imputed instead of the funding-type-quarter average. Results of these analyses are qualitatively similar and available upon request from the authors. Finally, the independent variable is scaled [0,100] to allow for an interpretation of our results as the causal effect of a 1 percentage point (p.p.) increase in the share of telemedicine on an outcome.

We note that telemedicine use is endogenous and is likely correlated with unobservable characteristics such as patient health. For example, a patient who uses a greater share of telemedicine may be doing so because they are unwell and therefore require frequent check-ins with their provider, which are more convenient using telemedicine. Alternatively, patients may be reserving telemedicine use for less serious conditions that they do not believe warrants an in-person visit, and therefore these patients would actually be healthier than their counterparts with a greater share of in-person procedures. To address these concerns, we use the cost-sharing waiver as an instrument for the share of procedures delivered via telemedicine in a given quarter:

$$ShareTele_{ift} = waiver_{ift} + \theta_i + \psi_t + \phi_{ift} \quad (10)$$

$$Y_{ift} = \widehat{ShareTele}_{ift} + \theta_i + \psi_t + \xi_{ift} \quad (11)$$

There are four assumptions underlying our instrumental variable approach: (1) conditional independence of the assignment of the instrument (i.e. that receipt of the cost-sharing waiver was uncorrelated with either the propensity to use telemedicine or the outcomes of interest, after conditioning on individual fixed effects); (2) the exclusion restriction must hold, meaning that the instrument can only affect the outcome variable through its effect on the share of telemedicine; (3) the instrument must have a strong effect on the endogenous variable; and (4) the effect of the instrument must be monotonic with respect to the endogenous variable (i.e. the cost-sharing waiver should only increase the share of telemedicine use, it should not result in a decrease in the share of telemedicine received) (Angrist & Pischke, 2009). The third condition can be tested by calculating the F-statistic of the excluded instrument, where excluded instruments with an F-statistic above 10 are typically considered strong (Andrews et al., 2019). The second assumption – that the instrument only affects our outcomes by changing the proportion of their services delivered virtually – is fundamentally untestable, though we note two theoretical violations. The first is that a cost-sharing waiver might affect spending and utilization outcomes by increasing the quantity of services received, as we explore in our difference-in-differences analysis. To address this concern, we estimate models holding the total quantity of services received constant. The second is that the cost-sharing waiver could result in an income effect, whereby saving money on medical services allows patients to spend money on other non-medical goods and services which could have an impact on their health. While we cannot test or account for this, Table 2 shows that cost-sharing savings are on the order of $30 per telemedicine service and that the average number of telemedicine services received per month is approximately 0.13, suggesting that the average savings are modest. This, in conjunction with the short amount of time that cost-sharing is waived, makes it unlikely that income-driven lifestyle changes will meaningfully impact health status as a result of the cost-sharing waiver.

6. RESULTS

6.1. Unadjusted Trends in Utilization and Expenditures

We begin by presenting summary statistics of key outcomes. Table 2 shows per-person per-month (PMPM) averages of utilization separately for those in fully-insured plans and self-insured plans, both before and after the COVID-19 pandemic. In addition, the percent change from the pre to post period is presented, as well as the unadjusted difference-in-differences. We note that, overall, the total number of services decreased as a result of the pandemic, as discussed in Section 2.3. Interestingly, prescription drug use increased for both groups, potentially mirroring the same substitution behavior between medical services and drugs that has been noted in the prior literature on substitution of medical services. (Chandra et al., 2021; Gaynor et al., 2007). Mental health utilization also increased by 1.9% for those in fully-insured firms and 4.6% for those in self-insured firms. The volume of psychotropics increased more than general prescription drugs, and psychotherapy utilization increased by 25.3% (21.2%) for those in fully-insured (self-insured) firms. Taken together, this seems to provide descriptive evidence that mental health deteriorated across the board during the pandemic, necessitating an increased use of mental health services (Czeisler et al., 2020; McGinty et al., 2020; Simon et al., 2020).

Of prime importance for our empirical strategy is out-of-pocket (OOP) spending for telemedicine procedures. We hypothesize that, given the cost-sharing waiver, we should see a large reduction in OOP spending for telemedicine services for those in fully-insured firms, but not for those in self-insured firms. Table 2 shows an 88% reduction in OOP spending for those in fully-insured firms and a 70% increase for those in self-insured. Figure 1 presents the trends on average OOP spending per telemedicine service over time. While we formally test for significance in the next section, the unadjusted trends provide compelling evidence that the waiver had the intended effect and that our empirical strategy is valid. Utilization associated with telemedicine spiked for those in fully-insured (self-insured) firms in the post-period, with telemedicine use increasing by 1,684% (1,391%) and telemental health increasing by 3,586% (3,115%). This can be seen in Figure 2 which plots the trends of monthly telemedicine and telemental health use per 1000 enrollees. The next sections present estimates from our formally implemented DD.

6.2. Effects of Cost-Sharing on Telemental Health Utilization

Crucial to the validity of our empirical strategy is that out-of-pocket (OOP) spending dropped substantially for those in fully-insured plans compared to those in self-insured plans. We provided compelling visual evidence for this in Figure 1 noting also that the trends in average OOP spending per telemedicine visit were approximately parallel for those in fully-insured and self-insured plans prior to the implementation of the cost-sharing waiver. Table 3 verifies this statistically using results from the estimation of equation (7), showing that the cost-sharing waiver caused an 87% reduction in the average OOP spending for telemedicine services.[6] Table 3 also includes results for total telemedicine services received per month and total telemental health services per month. We find an 18% increase in telemedicine use and a 14% increase in telemental health utilization attributable to the cost-sharing waiver. Interpreting the change in out-of-pocket spending as a change in the price[7], we use these percent changes to calculate the elasticity of demand for telemedicine and telemental health. The estimated elasticities are -0.21 and -0.16, respectively.

[6] Since the coefficient is sufficiently large that it cannot be interpreted as an approximate percent change, we exponentiate the coefficient to recover the ratio of incidence rate ratios and subtract 1 to get the exact percent change: $(e^{\beta}) - 1$.

[7] There is a literature on estimating elasticities using changes in non-linear health plan benefits. Normally, this literature assumes forward-looking patients who make assumptions about their anticipated end-of-year out-of-pocket spending and use the average OOP over the course of the year as the price per service, acknowledging that more OOP spending now will lead to less OOP spending later (i.e. after the deductible is reached) (Einav et al., 2015; Powell & Goldman, 2020). However, in this setting, since OOP spending is waived, spending in the present will not affect cost-sharing obligations in the future, so the scenario can be simplified to that of the myopic patient treating the spot-price of care as given. There is evidence that patients are more myopic than forward-looking in general (Brot-Goldberg et al., 2017).

In Table 4 we stratify our sample into those who had received treatment for mental illness prior the introduction of the cost-sharing waiver and those who had not. Each panel represents a different sample and dependent variable, corresponding to different types of mental disorders (see Appendix Table A1 for the diagnosis codes used to identify each disorder). The dependent variable for the “All Mental Illness” panel is the total number of monthly telemental health services for an individual, the “Depression” panel it is the total number of telemental health services for the treatment of depression, the “Anxiety” panel for the treatment of an anxiety disorder, etc. The two columns represent differences in samples. The first column contains individuals who did not receive any treatment for the given mental health disorder (either in-person or virtually) from January 2016-March 2020. The second column contains individuals who have had at least one claim that indicates treatment for the given disorder in that same time period. This table is meant to show whether the cost-sharing waiver is increasing access for those who previously received no treatment, or whether it is increasing treatment intensity for those who have already received treatment.

We note that the results from the ‘No Prior Treatment’ sample are based on an ex-post analysis. The reason for this is that, by construction, the counts for telemental health use are zero for both groups in the pre-period for this sample, which is inestimable via our Poisson regression. Further, since the analysis is ex-post, we are not able to include fixed effects as they are perfectly collinear with receipt of the cost-sharing waiver. The rationale behind the validity of this comparison is that, if we assume that there is a natural rate of developing mental illness and that the treatment decision to use telemental health is the same between enrollees in the fully-insured and self-insured plans in the absence of the cost-sharing waiver, then any difference in expected counts of telemental health should be attributable only to the waiver.

In the top panel we find an 13% increase in total telemental health use for those who had received prior treatment for a mental illness. There is no significant effect on those who had not previously received care at conventional significance levels, however there is a positive trend that is economically large for this group. We note substantial heterogeneity across the various disorders. For those having already received some form of treatment, we see significant increases of 28% for telemental treatment for depression, 29% for ADHD, and an insignificant increase of 8% for anxiety. Most strikingly, we find an 82% increase in the use of telemental healthcare for the treatment of serious mental illness for those already receiving treatment for serious mental illness.[8] While the estimate itself is subject to substantial noise owing to the rarity of the dependent variable (90% CI [0.48, 1.16]), even findings at the lower-end of the confidence interval are sizable, indicating approximately a 50% increase. While a high degree of price-sensitivity may indicate a high propensity for moral hazard, it is encouraging to see that it is those with serious mental illness who appear to increase their utilization the most, potentially indicating a positive benefit from reducing cost-sharing permanently. While there are economically large increases in virtual care use for those without prior treatment for all conditions except ADHD, the only statistically significant effect is found for new initiators of treatment for anxiety disorders. Figure 3 plots the coefficients and 90% confidence intervals from the results presented in Table 4.

6.3. Substitution Between Virtual and In-Person Services

Next, we explore whether telemental health is being used as a complement or a substitute for in-person services, as well as how this affects the total quantity of care received. If telemental health is being used as a perfect substitute we would expect an increase in virtual care to be accompanied by a corresponding decrease in in-person services, whereas if the two are complements, an increase in one should correspond to an increase in the other. Table 5 shows that those receiving the telemedicine cost-sharing waiver use 18% more telemedicine, though this is offset by a 9% reduction in in-person care, resulting in a net decrease of 8% in the quantity of care. Focusing on mental health specifically, we find a significant increase of 14% for telemental health services, a significant reduction of 9% for in-person mental health care, and no net change in the overall quantity of mental health services. A similar pattern holds for each individual mental illness. Overall, these results lead us to conclude that telemedicine is a near-perfect substitute for in-person care and that removing financial barriers to virtual care does not result in an increase in overall use, but rather a shift from one treatment modality to the other. Figure 4 plots the coefficients and 90% confidence intervals from the results presented in Table 5.

6.4.Heterogeneity of Effects by Race and Age

[8] Serious mental illness is defined as a person with schizophrenia, a schizoaffective disorder, manic depressive disorder, or bipolar disorder (Jaffe, 2019)

Next, we stratify the sample by race (Black, White, and Other Races) as well as age (Ages 5-26, 27-44, and 45-64). The results from Table 6 mirror those from Table 3. We find evidence of substantial heterogeneity in the reaction to the waiver. In particular, Black enrollees experience an increase in telemedicine and telemental health utilization that is 2-4 times larger than the effects for White enrollees. It is also of note that individual classified as "Other Race" appear to experience no effect from the cost-sharing waiver.[9] These results suggest that reducing financial barriers to receiving care have the potential to reduce disparities in access to care. It should be noted, however, that we are unable to control for income in our regressions. While our use of individual fixed effects should remove the confounding effects of any time-invariant income levels, the reduction in out-of-pocket spending is larger as a share of total income for those with low-income even though the level change is similar, which could explain why the same cost-sharing waiver could have heterogenous effects.

There is also interesting heterogeneity by age. Interestingly, it is the oldest group in our sample (ages 45-64) who experience the largest effect of the waiver, increasing their telemedicine and telemental health utilization by 26% and 23%, respectively. While young and middle-aged populations trend upwards in terms of using virtual services, the results are either insignificant or substantially smaller in magnitude than the near-elderly population.

6.5. Summary of results on the effects of removing cost-sharing

To summarize our findings on the effects of removing cost-sharing from telemedicine services, we show that the cost-sharing waiver resulted in significant changes in telemedicine and telemental health utilization for the full sample, with elasticities estimated as -0.21 and -0.16, respectively. While the use of virtual services increased substantially, this was completely offset by a corresponding decrease in in-person services, resulting in no change in the overall utilization for either the full sample or any subsample tested. Finally, we showed significant heterogeneity in results across various mental disorders, race, and age. Black enrollees, the near-elderly, and those with serious mental illness are the most likely to increase telemedicine and telemental health in response to the cost-sharing waiver. Overall, since waiving cost-sharing does not seem to increase overall quantity, but rather shifts the treatment modality from in-person to

[9] Other Race is composed primarily of individuals classified as Hispanic or Asian, with a small fraction being for those of unknown race.

online with quantity held constant, a natural follow-up question is how this shift affects more distal outcomes, such as treatment decisions, the probability of experiencing an adverse health event, and spending. The next sections address these new questions.

6.6.Impact of Telemedicine on Mental Health Treatment Decisions

This section explores the effects of the shift to telemedicine on mental health treatment decisions. We use the cost-sharing waiver as an instrument for the share of services received via telemedicine. This variable is rescaled from [0,1] to [0,100] to yield an interpretation of the 2SLS coefficients as the effect of a 1p.p. increase in the share of telemedicine services on the outcome variable. For treatment decisions for mental illness, we focus on utilization of psychotherapy and psychotropic medication.

Table 7 shows the effect of the share of telemedicine on the use of psychotherapy and psychotropics drugs both overall, and for those already under treatment for various mental illness. The results indicate that a 1p.p. increase in the share of services received virtually causes an increase in average quarterly psychotherapy visits of 0.004 (a 2.3% increase). It also results in an 0.163 decrease in the days supplied of psychotropic drugs per quarter (-1%), and a 0.363 decrease in total days supplied for all prescription medications (-0.3%). For scale, the cost sharing waiver results in approximately a 2p.p increase in the share of telemedicine services received, and approximately 10p.p. of all services are virtual during the pandemic in our sample. Therefore, a shift in treatment modality from in-person to online of the magnitude as that induced by the pandemic would result in a 10% decrease in the days supplied of psychotropics and a 23% increase in psychotherapy use.[10] Results are similar for subpopulations with identified mental illnesses.

These results indicate that, while the total quantity of mental health services does not seem to be affected by the use of telemedicine (see Table 5), the type of treatment received in the virtual setting may be much different than in the in-person setting. This could have implications for both the propensity to experience adverse health events and spending, as discussed in the next

[10] This approximate scaling assumes homogenous treatment effects. The actual estimate is of a local average treatment effect (LATE), which represents the causal effect on the compliers – those induced into using telemedicine by the cost-sharing waiver. This group may be substantially different than always-takers or never-takers, in which case scaling up the treatment effect proportionally would not be a good approximation (Angrist & Pischke, 2009).

sections. Figure 5 and Figure 6 plot the coefficients and 90% confidence intervals from the results presented in Table 7.

6.7. Telemedicine Use and Adverse Health Events

Table 8 shows that a 1p.p increase in the share of telemedicine results in a significant increase of 0.1p.p. in the probability of having an emergency department (ED) visit, though no change in the probability of an inpatient stay. This finding is persistent for all subpopulations of those with identified mental illnesses except those with serious mental illness, who show no change in the probability of use of either ED or inpatient care. While, small in absolute terms, this increase in the probability of ED use is large in relative terms, corresponding to a 3% increase in the probability of care for every 1p.p increase in the share of telemedicine. Based on equation (2), we interpret the increased probability of ED visits as a dwindling of health stock caused by an increase in the share of telemedicine. This finding is in contrast to Zeltzer et al. (2021) who find no increase in ED use caused by increased access to telemedicine. The simplest explanation for this discrepancy is that the two analyses use very different samples. Zeltzer and colleagues focus on patients in health maintenance organizations in Israel and with a focus on the primary care setting, whereas the present paper uses a US population enrolled in a variety of plan types and specifically report results for those seeking treatment for mental illness. Figure 8 plots the coefficients and 90% confidence intervals from the results of the ED analysis presented in Table 8.

6.8. Cost Considerations of Using Telemedicine

We next explore the effect of telemedicine on quarterly spending. The direction of spending is ambiguous a priori because there is some evidence that a service delivered via telemedicine is cheaper than an equivalent service provided in-person, implying the potential for cost-savings (Nord et al., 2019), though if the types of services received in telemedicine differ from those received in-person, or if telemedicine leads to more expensive downstream care then total spending may rise. As we have seen, treatment decisions differ for those receiving care in the virtual setting, and there is an increase in emergency department use, making the effect on spending a matter of empirical measurement. We present the effect of shifting to telemedicine on the log of spending for several categories of services in Table 9. We find that a 1p.p. increase in the share of telemedicine results in a 2.0% decrease in total spending. The effect is larger for those with ADHD and serious mental illness (-2.9% and -2.4% respectively). Interestingly, spending on mental health services does not appear to be changing, except in the case of those with ADHD, for whom it decreased by 2.2%. This suggests that the spending reductions are driven by changes in spending for medical-surgical procedures and not from mental health services or the decrease in psychotropic medications. Figure 9 plots the coefficients and 90% confidence intervals from the results presented in Table 9.

7. DISCUSSION

This paper presents analyses on two distinct, though related, streams of questions regarding the current state of telemedicine and mental health treatment in the COVID era. The first set of analyses addressed several questions regarding the effects of cost-sharing on telemedicine and telemental health utilization. There is a large literature on the effects of benefit design on utilization and health outcomes for various kinds of medical services going back to the RAND Health Insurance Experiment, and the estimates of these effects have had a strong influence on health policy both from the perspective of both payers and policymakers (Aron-Dine et al., 2013; Einav & Finkelstein, 2018; Manning et al., 1987, 1989). One result of these early studies was the justification for a two-tiered benefit structure for medical-surgical procedures and behavioral health procedures, with the latter receiving less generous benefits (e.g. greater cost-sharing obligations) (Barry et al., 2010). This was supported by the large estimated elasticity of demand for behavioral health services which implied a high degree of moral hazard for these services. The greater propensity for moral hazard that would impose negative externalities on members of the same risk pool, thereby reducing welfare (Ellis & McGuire, 1984; Feldstein, 1973; Manning et al., 1989; McGuire, 1986). One contribution of our work is measuring the elasticity of demand for telemental health, determining it be a relatively low -0.16 (compared to -0.80 for outpatient mental health care as determined in the RAND HIE[11]), suggesting that moral hazard is unlikely to be as large of concern (Manning et al., 1989). We saw the largest effects concentrated among

[11] The RAND HIE estimate is of the arc elasticity of demand for outpatient mental health services, using differences in utilization between those randomized to the 95% coinsurance rate group and the 25% coinsurance rate group (with no deductibles or copays). Our estimate is of the textbook definition of elasticity of demand, which differs slightly from the arc elasticity. Additionally, our source of cost-sharing is the sum of the deductible, copay, and coinsurance, which is not perfectly consistent with the methodology used in the HIE. While the two methods may have slight variations, it is unlikely that the difference in methodology alone would result in the drastic difference we observe.

black individuals, the near elderly, and those with serious mental illness. While the larger effects may lead to concerns of overuse, these concerns may be partially offset by the unique advantages associated with increasing access to care for these particular groups during the study period, such as insulating the elderly from in-person contact during a pandemic and reducing well-documented inequities in access to healthcare in the black community (Ndugga & Artiga, 2021).

Additionally, while we show an increase in the use of virtual services stemming from reduced cost-sharing, the increased quantity was completely offset by a reduction in in-person services, resulting in no change in the total quantity of services received. While the telemedicine cost-sharing reductions did not appear to increase access to mental health services as hoped, it is possible that it could still be welfare-enhancing in terms of providing convenience and reducing both financial and non-financial burdens for individual patients, such as travel time or provider search costs.

The second stream of questions we explored involved estimating the effects of shifting care modalities from the in-person setting to telemedicine. This analysis is important as telemedicine is poised to maintain its new foothold, permanently changing the way care is delivered. We present results of the effect of moving to the virtual environment on treatment decisions, spending, and adverse health outcomes. Perhaps our most striking finding is the degree to which treatment decisions are influenced by the environment in which a patient sought care. We report a significant increase in the use of psychotherapy and sizeable reductions in the days-supplied of prescription medications (particularly psychotropic medications) attributable to an exogenous increase in the share of procedures performed via telemedicine.

We show that an increase in the share of telemedicine causes a higher propensity to use emergency services. While this may suggest that substituting in-person care for telemedicine results in worse health outcomes, we note that we do not observe a corresponding increase in the probability of an inpatient admission. Further study is needed to understand the mechanisms driving this increased use of emergency services. Two avenues that are particularly interesting to investigate are whether there are differences in the providers that deliver virtual care compared to those in brick-and-mortar settings. For example, it may be the case that patients are more likely to see licensed social workers for the treatment of mental illness if they get care online, whereas they are more likely to get care from a primary care provider (i.e. a physician) in-person. While the increase in ED use is worrying, there also appears to be a modest cost-savings associated with an increased share of telemedicine. These cost-savings do not appear to come from mental health services or psychotropic medications, suggesting that there are changes in spending on medical-surgical services resulting from the shift to telemedicine. It is unclear if these cost-savings come from improved efficiency in the delivery of virtual care (e.g. lower overhead costs compared to a physical office space) or whether they are driven by patients foregoing in-person services that may have been clinically warranted.

We note several limitations to our study. First, our findings are subject to limitations common to studies using claims data, including an inability to observe clinical characteristics of the patients. While we address any individual-level time-invariant confounders using fixed effects, it is likely that there are time-varying unobservable characteristics that we could not account for. Further, we cannot observe services that patients received that did not have claim filed. This is particularly problematic in studying mental health treatments as up to half of psychiatrists and psychologists do not accept any form of insurance (Bishop et al., 2014). While many of these claims for providers that do not accept insurance may still be filed as "out-of-network" claims and therefore still appear in our data, it is impossible to know how many are never documented. We are also limited by our inability to see any action that individual firms took to help their employees during the pandemic that are unrelated to plan benefits. For example, a firm may have contracted with digital mental health services, improving their employees' access to care. While we cannot observe this in our data, other studies have failed to find evidence that benefits are systematically more or less generous at self-insured firms, either in terms of plan benefits or in their offering of supplemental wellness programs (Eibner et al., 2011). Finally, our study period corresponds to the height of the 2020 COVID-19 pandemic and likely estimated the effects under a set of conditions that are unlikely to persist in the long-term. Therefore, our results may not generalize into the post-pandemic landscape and researchers should continue to study the effects of cost-sharing arrangements and telemedicine use as the population settles into the new equilibrium.

Overall, the shock to our healthcare system from COVID-19 and the explosion of demand for telemedicine offers an exciting opportunity to restructure healthcare delivery and rechart its trajectory. Policymakers and practitioners should be ready to adapt and make adjustments as new data becomes available. Telemedicine has the potential to expand access to treatment for those facing a variety of barriers to care. We present evidence that encouraging telemedicine use does not result in a greater degree of overall utilization, but rather a shift in care settings from in-person to virtual. This shift to telemedicine results in different treatment decisions regarding the treatment of mental illness, with those induced into using telemedicine making greater use of psychotherapy and less use of psychotropic medications. Greater telemedicine use also appears to substantially reduce overall expenditures. However, this reduction in cost must be weighed against the higher propensity to use emergency department services, potentially suggesting worse health outcomes. More research is required to understand the mid and long-term effects that shifting to virtual care has on health outcomes and spending. While there is much to be optimistic about with the rapid expansion of telemedicine services, practitioners and policymakers should exercise caution in replacing existing in-person care with virtual care until more is understood about how it impacts treatment decisions and patient health.

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Table 1: Sample Baseline Summary Statistics

	Fully-Insured	Self-Insured
Demographics		
Age	36.92 (18.01)	35.03 (17.73)
CCW Comorbidities	1.84 (2.5)	1.8 (2.39)
Sex		
Female	51.90%	48.40%
Male	48.10%	51.60%
Race		
Asian	5.50%	7.50%
Black	15.20%	8.10%
Hispanic	17.30%	15.40%
White	58.70%	66.20%
Race Unknown	3.40%	2.80%
Census Division		
East North Central	1.70%	4.70%
East South Central	2.30%	6.10%
Mid Atlantic	3.40%	7.40%
Mountain	6.20%	13.50%
New England	0.70%	1.60%
Pacific	12.10%	12.80%
South Atlantic	33.80%	12.60%
West North Central	3.20%	9.50%
West South Central	36.60%	31.80%
Baseline Monthly Mental Health Treatment		
% With Mental Health Services	4.70%	5.10%
% With Depression Services	1.50%	1.60%
% With Anxiety Services	2.70%	3%
% With ADHD Services	0.90%	0.90%
% With Serious Mental Illness Services	0.20%	0.20%
Utilization		
Monthly Services	3.272 (12.232)	3.384 (12.347)
% With Any Services	30.90%	32.80%
N	3,109,212	10,012,788
Firms	310	474
Plans	1185	2746
Employees per firm	375.69 (1265.11)	847.68 (1780.71)

Notes: Unit of observation is the person-month. Baseline period refers to January 2018-March 2020 which constitutes the pre-period in the analysis. CCW refers to the chronic condition warehouse comorbidity index, which is calculated using the full pre-COVID medical history for a patient spanning January 2016-March 2020. Statistics describe a continuously enrolled sample

Table 2: Summary statistics of key outcomes stratified by funding-type and time-period

	Fully Insured					Self Insured					DID
	Pre-COVID	**SD**	**Post-COVID**	**SD**	**% Δ**	**Pre-COVID**	**SD**	**Post-COVID**	**SD**	**% Δ**	**% ΔΔ**
Utilization											
Total Services	3.272	(12.23)	2.722	(11.64)	-16.8%	3.384	(12.35)	3.052	(13.14)	-9.8%	-6.5%
In-Person Services	3.264	(12.23)	2.582	(11.54)	-20.9%	3.375	(12.34)	2.926	(13.04)	-13.3%	-7.0%
Telemedicine Services	0.008	(0.15)	0.140	(0.81)	1684.3%	0.008	(0.16)	0.126	(0.83)	1391.0%	180.5%
Rx Days Supplied	37.750	(82.26)	40.927	(89.85)	8.4%	32.789	(75.13)	36.153	(82.54)	10.3%	-0.5%
Mental Health Utilization											
Mental Health Services	0.238	(3.17)	0.243	(3.14)	1.9%	0.267	(3.3)	0.279	(3.49)	4.6%	-3.1%
In-Person MH Services	0.236	(3.17)	0.179	(3.03)	-24.1%	0.265	(3.3)	0.219	(3.38)	-17.2%	-4.5%
Telemental Health Services	0.002	(0.08)	0.063	(0.63)	3585.8%	0.002	(0.1)	0.060	(0.67)	3114.7%	189.1%
Psychotropic Days Supplied	5.425	(22.19)	6.090	(25.26)	12.2%	5.105	(20.9)	5.868	(23.69)	14.9%	-1.9%
Psychotherapy Sessions	0.050	(0.58)	0.063	(0.57)	25.3%	0.055	(0.54)	0.067	(0.58)	21.2%	1.9%
Adverse Health Events											
Any Emergency Department Use	0.013	(0.11)	0.011	(0.11)	-14.6%	0.019	(0.14)	0.016	(0.13)	-15.4%	6.6%
Any Inpatient Admission	0.007	(0.08)	0.007	(0.08)	8.2%	0.007	(0.08)	0.008	(0.09)	12.0%	-4.4%
Expenditures											
Monthly Spending	590.339	(5210.75)	547.750	(4971.41)	-7.2%	645.508	(5621.4)	611.180	(5678.65)	-5.3%	-1.3%
Monthly MH Spending	37.486	(944.15)	42.300	(1081.65)	12.8%	46.193	(1245.39)	55.223	(1502.5)	19.5%	-10.1%
Monthly Telemedicine Spending	0.403	(8.96)	12.130	(74.28)	2911.4%	0.408	(10.17)	9.171	(92.36)	2147.4%	731.2%
Average OOP Per Service	24.522	(62.57)	18.428	(54.94)	-24.9%	31.564	(68.71)	27.253	(61.56)	-13.7%	-6.4%
Average OOP Per Telemedicine Service	13.855	(25.02)	1.660	(13.12)	-88.0%	18.254	(31.88)	31.098	(45.18)	70.4%	-156.0%

Notes: Pre-COVID represents the time-period from January 2018 – March 2020. Post-COVID represents April 2020 – September 2020, which is the analytic time period because the telemedicine cost-sharing waiver for those in fully-insured plans went into effect on April 1, 2020 and expired on October 1, 2020. Statistics presented represent person-month averages from a continuously-enrolled sample, with standard deviations presented in parenthesis in the adjacent column. Percent differences show the percent change for going from the pre-period to the post-period for those in fully-insured plans and self-insured plans. The difference-in-difference is the unconditional change in means for those in fully-insured plans minus the change in means for those in self-insured plans divided by the simple average of the pre-period means for the fully-insured and self-insured participants.

Table 3: Effect of cost-sharing waiver on telemedicine and telemental health utilization

	(1) Telemedicine OOP	(2) Telemedicine	(3) Telemental Health
$\widehat{\beta^{DD}}$	-2.003***	0.180**	0.137**
	(0.160)	(0.077)	(0.057)
Mean	29.021	0.107	0.171
Observations	133207	4537269	1174734
Individual FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of analysis is the person-month. Coefficients represent the natural log of the ratio of incidence rate ratios between those in fully-insured and self-insured firms in the post and pre-periods. The interpretation is that 100 times $\widehat{\beta^{DD}}$ is the approximate percent change for causally attributable to the cost-sharing waiver for small values of $\widehat{\beta^{DD}}$. A precise estimate of the percent change can be calculated by exponentiating the coefficient, subtracting 1, and multiplying by 100. The total observations vary between models despite the analytic sample being the same because observations with no within-panel variation in the dependent variable are automatically excluded as they do not provide meaningful information and prohibit estimation via the Poisson pseudo-maximum likelihood estimator. The reported means are the means for the observations that remain in each model. For means for the entire sample (inclusive of those who have no within-panel variation) see Table 1. Estimates are from the ppmlhdfe Stata command (Correia et al., 2020).

Table 4: Stratification of effects by those with or without prior mental illness

	(1) No Prior Treatment	(2) Prior Treatment
	Monthly Virtual Services	Monthly Virtual Services
All Mental Illness		
$\widehat{\beta^{DD}}$	0.150	0.126**
	(0.107)	(0.057)
Mean	0.0082	0.1808
Observations	2155914	1009602
Depression		
$\widehat{\beta^{DD}}$	0.058	0.275***
	(0.110)	(0.079)
Mean	0.0034	0.1648
Observations	2638002	340032
Anxiety		
$\widehat{\beta^{DD}}$	0.197*	0.076
	(0.104)	(0.067)
Mean	0.0070	0.1669
Observations	2414658	589644
ADHD		
$\widehat{\beta^{DD}}$	-0.200	0.291***
	(0.137)	(0.102)
Mean	0.0010	0.1149
Observations	2778828	230142
Serious Mental Illness		
$\widehat{\beta^{DD}}$	0.290	0.816***
	(0.207)	(0.206)
Mean	0.0004	0.2044
Observations	2885064	53658
Individual FE	No	Yes
Month FE	Yes	Yes
Research Design	Ex-Post	DD

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of analysis is the person-month. Coefficients represent the natural log of the ratio of incidence rate ratios between those in fully-insured and self-insured firms in the post and pre-periods. The interpretation is that 100 times $\widehat{\beta^{DD}}$ is the approximate percent change for causally attributable to the cost-sharing waiver for small values of $\widehat{\beta^{DD}}$. A precise estimate of the percent change can be calculated by exponentiating the coefficient, subtracting 1, and multiplying by 100. The 'No Prior Treatment' subsamples represents those who had no claims which would indicate diagnosis or treatment of a given condition from January 2016-March 2020. The 'Prior Treatment' subsample had at least 1 claim indicating diagnosis or treatment of a given condition. The dependent variable in each case in the monthly counts of telemedicine services for the treatment of a given condition (e.g. telemedicine for the treatment of depression). Definitions for how each condition is identified in claims data is available in Appendix Table A1. Observations with no within-panel variation in the dependent variable are automatically excluded as they do not provide meaningful information and prohibit estimation via the Poisson pseudo-maximum likelihood estimator. The reported means are the means for the observations that remain in each model. Estimates are from the ppmlhdfe Stata command (Correia et al., 2020).

Table 5: Substitution between use of tele and in-person mental health services

	(1) Virtual Services	(2) In-Person Services	(3) Total Services
All Services			
$\widehat{\beta^{DD}}$	0.180**	-0.091***	-0.081***
	(0.077)	(0.020)	(0.018)
Mean	0.107	3.483	3.511
Observations	4537269	14996817	15014934
All Mental Illness			
$\widehat{\beta^{DD}}$	0.137**	-0.086***	-0.027
	(0.057)	(0.030)	(0.025)
Mean	0.1709	0.8802	0.9049
Observations	1174734	4544166	4641780
Depression			
$\widehat{\beta^{DD}}$	0.254***	-0.078*	-0.014
	(0.077)	(0.041)	(0.037)
Mean	0.1557	0.7413	0.7580
Observations	418473	1682571	1731411
Anxiety			
$\widehat{\beta^{DD}}$	0.104	-0.107***	-0.031
	(0.066)	(0.038)	(0.029)
Mean	0.1551	0.6780	0.6933
Observations	746526	3066789	3166053
ADHD			
$\widehat{\beta^{DD}}$	0.254**	-0.125**	-0.039
	(0.099)	(0.053)	(0.041)
Mean	0.1138	0.5922	0.6160
Observations	258687	805959	822558
Serious Mental Illness			
$\widehat{\beta^{DD}}$	0.805***	-0.149	-0.049
	(0.204)	(0.113)	(0.091)
Mean	0.1956	1.0972	1.1305
Observations	62238	187407	192654
Individual FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of analysis is the person-month. Coefficients represent the natural log of the ratio of incidence rate ratios between those in fully-insured and self-insured firms in the post and pre-periods. The interpretation is that 100 times $\widehat{\beta^{DD}}$ is the approximate percent change for causally attributable to the cost-sharing waiver for small values of $\widehat{\beta^{DD}}$. A precise estimate of the percent change can be calculated by exponentiating the coefficient, subtracting 1, and multiplying by 100. The dependent variable in (1) is the monthly counts of telemedicine services for the treatment of a given condition (e.g. telemedicine for the treatment of depression). The dependent variable in (2) is the monthly count of in-person services for a given condition, and (3) is the sum of (1) and (2). Definitions for how each condition is identified in claims data is available in Appendix Table A1. Observations with no within-panel variation in the dependent variable are automatically excluded as they do not provide meaningful information and prohibit estimation via the Poisson pseudo-maximum likelihood estimator. The reported means are the means for the observations that remain in each model. Estimates are from the ppmlhdfe Stata command (Correia et al., 2020).

Table 6: Effect of cost-sharing waiver on telemedicine and telemental health utilization, by race and age

	(1) Telemedicine OOP	(2) Telemedicine	(3) Telemental Health
Panel A: By Race			
A1: Black			
$\widehat{\beta^{DD}}$	-2.182***	0.535***	0.580***
	(0.264)	(0.131)	(0.133)
Mean	24.233	0.105	0.162
Observations	11519	455433	97944
Adj. R-Squared	0.606	0.405	0.561
A2: White			
$\widehat{\beta^{DD}}$	-1.918***	0.231***	0.133**
	(0.161)	(0.073)	(0.059)
Mean	29.473	0.109	0.170
Observations	93995	3051246	863610
Adj. R-Squared	0.609	0.436	0.594
A3: Other Race			
$\widehat{\beta^{DD}}$	-2.240***	-0.135	-0.063
	(0.257)	(0.083)	(0.122)
Mean	29.477	0.102	0.179
Observations	27693	1030590	213180
Adj. R-Squared	0.626	0.424	0.594
Panel B: By Age			
B1: Young (5-26)			
$\widehat{\beta^{DD}}$	-1.430***	0.108	0.141*
	(0.179)	(0.072)	(0.082)
Mean	31.309	0.131	0.225
Observations	35194	1139094	428010
Adj. R-Squared	0.637	0.557	0.622
B2: Middle Aged (27-44)			
$\widehat{\beta^{DD}}$	-2.167***	0.132*	0.028
	(0.196)	(0.079)	(0.085)
Mean	27.325	0.105	0.155
Observations	41088	1261953	335940
Adj. R-Squared	0.593	0.374	0.556
B3: Near Elderly (45-64)			
$\widehat{\beta^{DD}}$	-2.383***	0.259***	0.231***
	(0.230)	(0.094)	(0.084)
Mean	28.830	0.096	0.128
Observations	56925	2136222	410784
Adj. R-Squared	0.613	0.379	0.558
Individual FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of analysis is the person-month. Coefficients represent the natural log of the ratio of incidence rate ratios between those in fully-insured and self-insured firms in the post and pre-periods. The interpretation is that 100 times $\widehat{\beta^{DD}}$ is the approximate percent change for causally attributable to the cost-sharing waiver for small values of $\widehat{\beta^{DD}}$. A precise estimate of the percent change can be calculated by exponentiating the coefficient, subtracting 1, and multiplying by 100. The total observations vary between models despite the analytic sample being the same because observations with no within-panel variation in the dependent variable are automatically excluded as they do not provide meaningful information and prohibit estimation via the Poisson pseudo-maximum likelihood estimator. The reported means are the means for the observations that remain in each model. For means for the entire sample (inclusive of those who have no within-panel variation) see Table 1. Estimates are from the ppmlhdfe Stata command (Correia et al., 2020).

Table 7: Effects of shifting from in-person to telemedicine on psychotherapy and prescription drug use

	(1) Quarterly Psychotherapy Sessions	(2) Quarterly Psychotropic Days Supplied	(3) Quarterly Rx Days Supplied
Full Sample			
Share Telemedicine (Δ 1p.p.)	0.004**	-0.163***	-0.363***
	(0.002)	(0.040)	(0.1204)
Mean	0.1714	16.1634	104.7328
First-Stage F-Stat	3139.6855	3139.6855	3139.6855
Observations	5833692	5833692	5833692
Any Mental Illness			
Share Telemedicine (Δ 1p.p.)	0.012**	-0.409***	-1.014***
	(0.005)	(0.130)	(0.298)
Mean	0.6264	52.1797	185.1385
First-Stage F-Stat	472.2918	472.2918	472.2918
Observations	1544508	1544508	1544508
Depression			
Share Telemedicine (Δ 1p.p.)	0.007	-0.597**	-1.805***
	(0.010)	(0.240)	(0.506)
Mean	0.9915	83.5361	249.2425
First-Stage F-Stat	198.9078	198.9078	198.9078
Observations	566134	566134	566134
Anxiety			
Share Telemedicine (Δ 1p.p.)	0.012*	-0.425**	-0.921**
	(0.007)	(0.165)	(0.359)
Mean	0.8212	58.3503	197.0855
First-Stage F-Stat	318.7266	318.7266	318.7266
Observations	1023797	1023797	1023797
ADHD			
Share Telemedicine (Δ 1p.p.)	0.022*	-0.379	-1.439**
	(0.012)	(0.337)	(0.581)
Mean	0.7660	80.7703	163.0573
First-Stage F-Stat	74.8627	74.8627	74.8627
Observations	278408	278408	278408
Serious Mental Illness			
Share Telemedicine (Δ 1p.p.)	0.027	-0.805	-2.623**
	(0.021)	(0.641)	(1.266)
Mean	1.7287	130.5665	325.6573
First-Stage F-Stat	36.7767	36.7767	36.7767
Observations	63006	63006	63006

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of analysis is the person-quarter. The independent variable is the share of procedures received via telemedicine in a given quarter. If no services are received, the average share of telemedicine for the funding-type-quarter is imputed (i.e. if the enrollee is in a fully-insured (self-insured) plan, the average share for those in fully-insured (self-insured) plans in the same quarter is imputed). Sensitivity analyses are performed which either omit observations where no services are received (32% of sample) or where 0 is imputed instead of the funding-type-quarter average. Results of these analyses are available upon request from the authors. The independent variable is scaled [0,100]. The independent variable is instrumented with a binary variable for receipt of the telemedicine cost-sharing waiver in a given quarter. Kleibergen-Paap F-statistics of the excluded instrument are reported as a test of instrument strength. Models are estimated via two-stage least-squares using the xtivreg2 Stata command (Baum et al., 2007). Models are estimated with individual fixed-effects with standard errors clustered at the individual-level to adjust for autocorrelation between repeated observations of the same individual over time. Coefficients are interpreted as the causal effect of a 1p.p increase in the share of telemedicine procedures on the outcome. The dependent variable in model (1) is the count of services for psychotherapy at the person-quarter level. Procedure codes identifying psychotherapy can be found in Appendix Table A1. The dependent variable in model (2) is the days supplied of psychotropic drugs at the person-quarter level. Days supply is the sum of the days supply of all psychotropics (i.e. the quarterly days supply can exceed 90 if the patient is on multiple psychotropic medications). Psychotropic medications are determined using the American Hospital Formulary System clinical drug classification system, as described in Appendix Table A1. Model (3) is similar to (2) but includes all prescription drugs. Panel 2-6 presents results from subsamples with at least one indicator for the given disorder between January 2016 and March 2020.

Table 8: Effects of using telemedicine on inpatient and ED psychiatric use

	(1) Any Inpatient Care	(2) Any ED Care
Full Sample		
Share Telemedicine (Δ 1p.p.)	0.0001	0.0011***
	(0.0001)	(0.0002)
Mean	0.0176	0.0345
First-Stage F-Stat	3139.6855	3139.6855
Observations	5833692	5833692
Any Mental Illness		
Share Telemedicine (Δ 1p.p.)	-0.0002	0.0016***
	(0.0003)	(0.0004)
Mean	0.0333	0.0524
First-Stage F-Stat	472.2918	472.2918
Observations	1544508	1544508
Depression		
Share Telemedicine (Δ 1p.p.)	-0.0005	0.0020***
	(0.0005)	(0.0006)
Mean	0.0461	0.0613
First-Stage F-Stat	198.9078	198.9078
Observations	566134	566134
Anxiety		
Share Telemedicine (Δ 1p.p.)	-0.0001	0.0014***
	(0.0004)	(0.0005)
Mean	0.0360	0.0567
First-Stage F-Stat	318.7266	318.7266
Observations	1023797	1023797
ADHD		
Share Telemedicine (Δ 1p.p.)	-0.0002	0.0015**
	(0.0006)	(0.0007)
Mean	0.0268	0.0420
First-Stage F-Stat	74.8627	74.8627
Observations	278408	278408
Serious Mental Illness		
Share Telemedicine (Δ 1p.p.)	-0.0013	0.0002
	(0.0012)	(0.0011)
Mean	0.0921	0.0627
First-Stage F-Stat	36.7767	36.7767
Observations	63006	63006

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of analysis is the person-quarter. The independent variable is the share of procedures received via telemedicine in a given quarter. If no services are received, the average share of telemedicine for the funding-type-quarter is imputed (i.e. if the enrollee is in a fully-insured (self-insured) plan, the average share for those in fully-insured (self-insured) plans in the same quarter is imputed). Sensitivity analyses are performed which either omit observations where no services are received (32% of sample) or where 0 is imputed instead of the funding-type-quarter average. Results of these analyses are available upon request from the authors. The independent variable is scaled [0,100]. The independent variable is instrumented with a binary variable for receipt of the telemedicine cost-sharing waiver in a given quarter. Kleibergen-Paap F-statistics of the excluded instrument are reported as a test of instrument strength. Models are estimated via two-stage least-squares using the xtivreg2 Stata command (Baum et al., 2007). Models are estimated with individual fixed-effects with standard errors clustered at the individual-level to adjust for autocorrelation between repeated observations of the same individual over time. The dependent variables in both models are binary indicators for whether the individual had (1) an inpatient admission or (2) an emergency department visit in that quarter. Coefficients can be interpreted as the percentage point change in the probability of having an inpatient or ED admission in a quarter caused by a 1p.p. increase in the share of telemedicine. Panel 2-6 present results from subsamples with at least one indicator for the given disorder between January 2016 and March 2020.

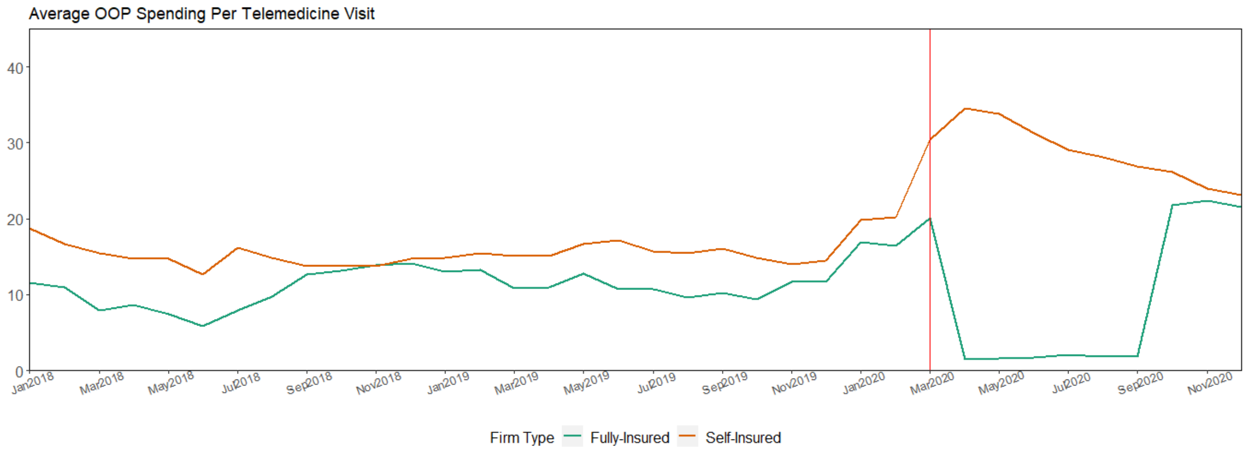
Table 9: Effects of shifting from in-person to telemedicine on spending

	(1) Log (Tele Spending)	(2) Log (MH Spending)	(3) Log (Total Spending)
Full Sample			
Share Telemedicine (Δ 1p.p.)	0.064***	0.002	-0.020***
	(0.002)	(0.002)	(0.002)
Mean	8.1837	141.0218	1907.3840
First-Stage F-Stat	3139.69	3139.69	3139.69
Observations	5833692	5833692	5833692
Any Mental Illness			
Share Telemedicine (Δ 1p.p.)	0.125***	0.006	-0.013***
	(0.005)	(0.004)	(0.004)
Mean	19.5831	503.9515	3398.9990
First-Stage F-Stat	472.29	472.29	472.29
Observations	1544508	1544508	1544508
Depression			
Share Telemedicine (Δ 1p.p.)	0.131***	-0.001	-0.012**
	(0.008)	(0.007)	(0.006)
Mean	26.6268	822.9392	4248.1778
First-Stage F-Stat	198.91	198.91	198.91
Observations	566134	566134	566134
Anxiety			
Share Telemedicine (Δ 1p.p.)	0.123***	0.007	-0.012**
	(0.006)	(0.005)	(0.005)
Mean	22.3468	576.7727	3557.9094
First-Stage F-Stat	318.73	318.73	318.73
Observations	1023797	1023797	1023797
ADHD			
Share Telemedicine (Δ 1p.p.)	0.107***	-0.022*	-0.029***
	(0.009)	(0.012)	(0.010)
Mean	23.2201	771.8918	2481.5238
First-Stage F-Stat	74.86	74.86	74.86
Observations	278408	278408	278408
Serious Mental Illness			
Share Telemedicine (Δ 1p.p.)	0.094***	-0.017	-0.024*
	(0.014)	(0.015)	(0.014)
Mean	40.4944	1906.5670	5235.9200
First-Stage F-Stat	36.78	36.78	36.78
Observations	63006	63006	63006

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of analysis is the person-quarter. The independent variable is the share of procedures received via telemedicine in a given quarter. If no services are received, the average share of telemedicine for the funding-type-quarter is imputed (i.e. if the enrollee is in a fully-insured (self-insured) plan, the average share for those in fully-insured (self-insured) plans in the same quarter is imputed). Sensitivity analyses are performed which either omit observations where no services are received (32% of sample) or where 0 is imputed instead of the funding-type-quarter average. Results of these analyses are available upon request from the authors. The independent variable is scaled [0,100]. The independent variable is instrumented with a binary variable for receipt of the telemedicine cost-sharing waiver in a given quarter. Kleibergen-Paap F-statistics of the excluded instrument are reported as a test of instrument strength. Models are estimated via two-stage least-squares using the xtivreg2 Stata command (Baum et al., 2007). Models are estimated with individual fixed-effects with standard errors clustered at the individual-level to adjust for autocorrelation between repeated observations of the same individual over time. The dependent variables are the natural logarithm of the quarterly spending on (1) telemedicine services, (2) mental health services, and (3) all services. Spending on mental health services also includes spending on psychotropic medication. Psychotropic medications are determined using the American Hospital Formulary System clinical drug classification system, as described in Appendix Table A1. Overall spending also includes spending on

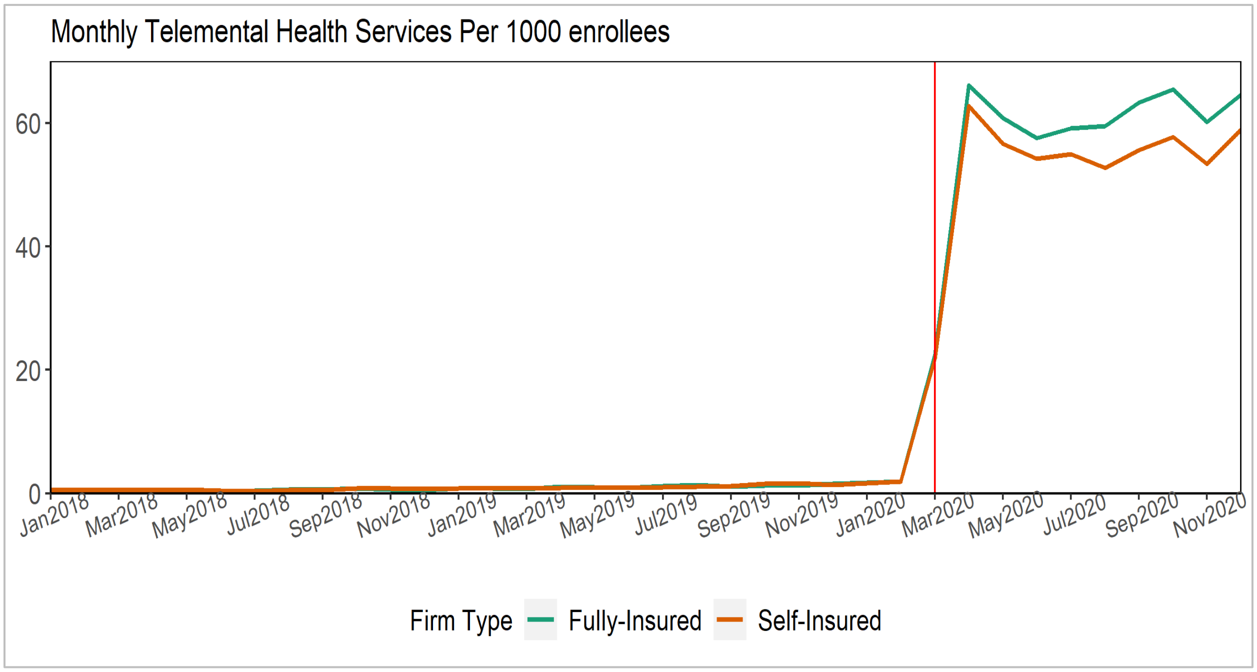
all medications. Coefficients can be interpreted as the percentage change in quarterly spending caused by a 1p.p. increase in the share of telemedicine. Panel 2-6 present results from subsamples with at least one indicator for the given disorder between January 2016 and March 2020.

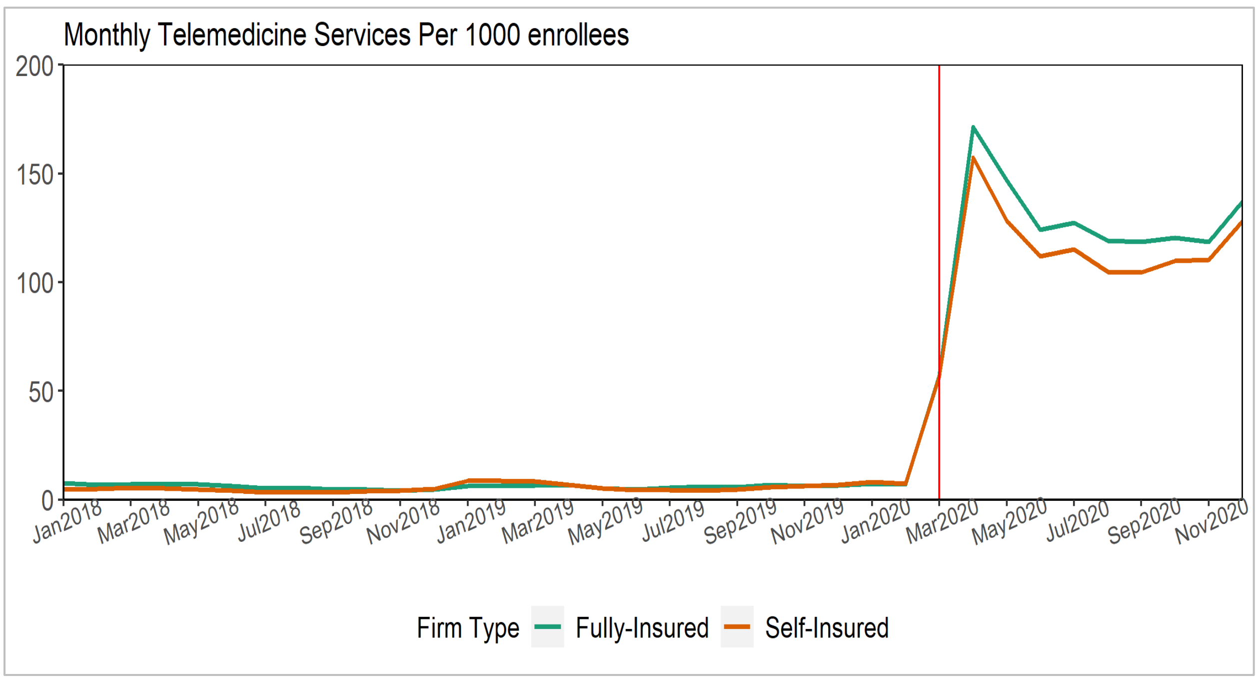
Figure 1: Average out-of-pocket spending per telemedicine visit over time



Notes: Trends over time for the average out-of-pocket spending on a telemedicine claim. For the definition of a telemedicine claim see Appendix Table A1. Out-of-pocket spending is defined as the sum of the deductible, coinsurance, and copay on the claim. The red line is overlaid on March 2020, the month before the telemedicine cost-sharing waiver went into effect for those in fully-insured firms. The cost-sharing waiver was reintroduced in October 2020.

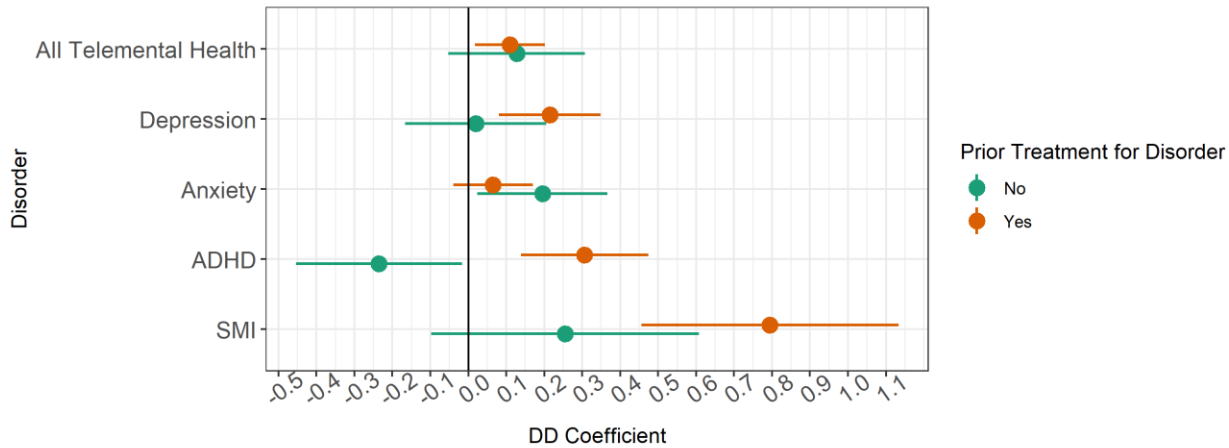
Figure 2: Monthly trends in telemedicine use per 1000 enrollees





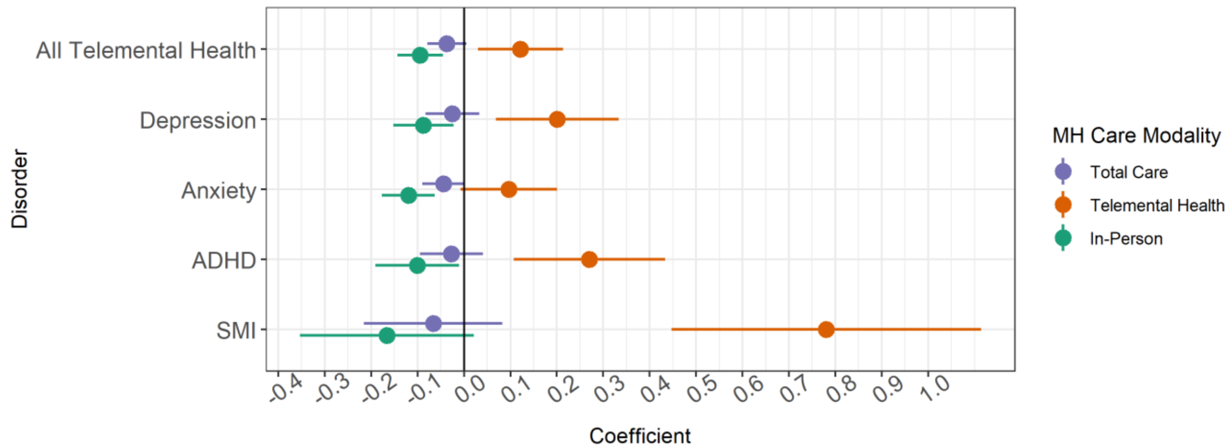
Notes: Trends over time for the average count of monthly for telemental health (top) and telemedicine (bottom) per 1000 enrollees. For the definition of a telemedicine and telemental health see Appendix Table A1. The red line is overlaid on March 2020, the month before the telemedicine cost-sharing waiver went into effect for those in fully-insured firms. The cost-sharing waiver was reintroduced in October 2020.

Figure 3: Stratification of effects by those with or without prior mental illness



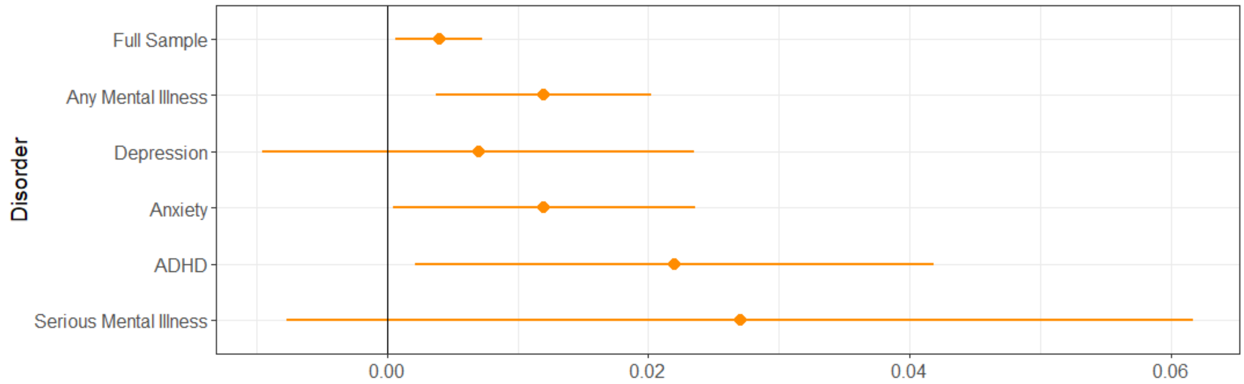
Notes: The points correspond to the coefficients in Table 4, with the whiskers representing the 90% confidence interval. See Table 4 for analytic notes.

Figure 4: Substitution between use of tele and in-person mental health services



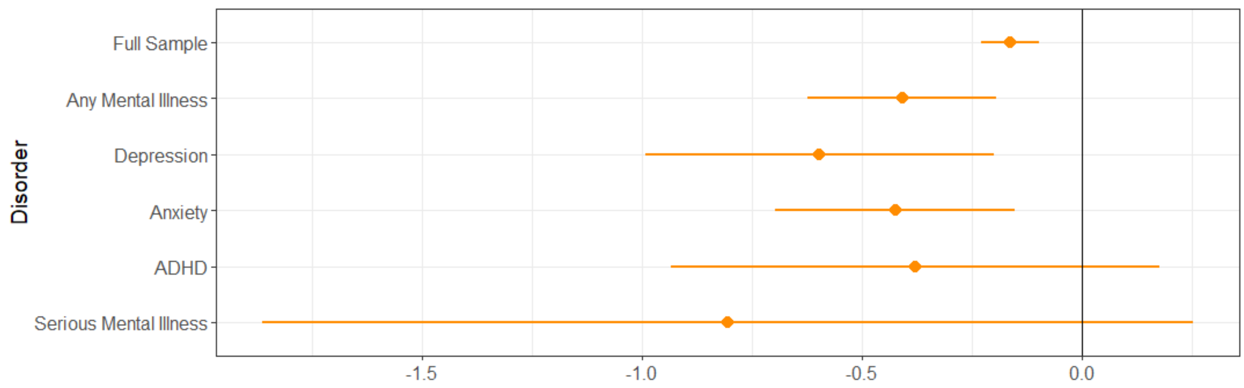
Notes: The points correspond to the coefficients in Table 5, with the whiskers representing the 90% confidence interval. See Table 5 for analytic notes.

Figure 5: Effects of shifting from in-person to telemedicine on psychotherapy use



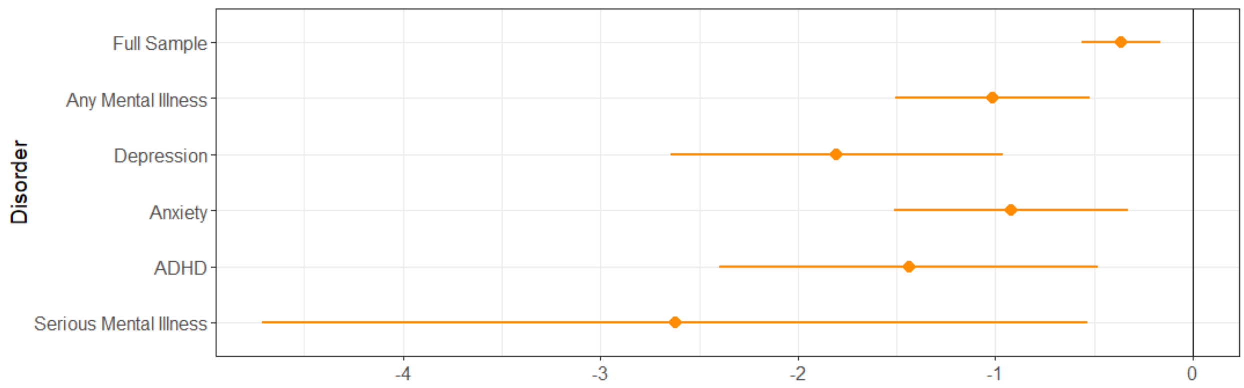
Notes: The points correspond to the coefficients in Table 7, with the whiskers representing the 90% confidence interval. See Table 7 for analytic notes.

Figure 6: Effects of shifting from in-person to telemedicine psychotropic drug use



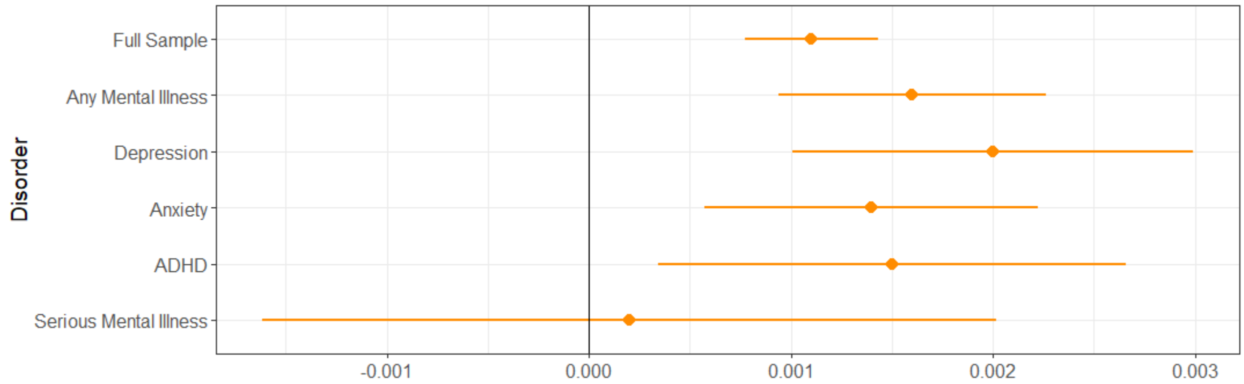
Notes: The points correspond to the coefficients in Table 7, with the whiskers representing the 90% confidence interval. See Table 7 for analytic notes.

Figure 7: Effects of shifting from in-person to telemedicine on prescription drug use



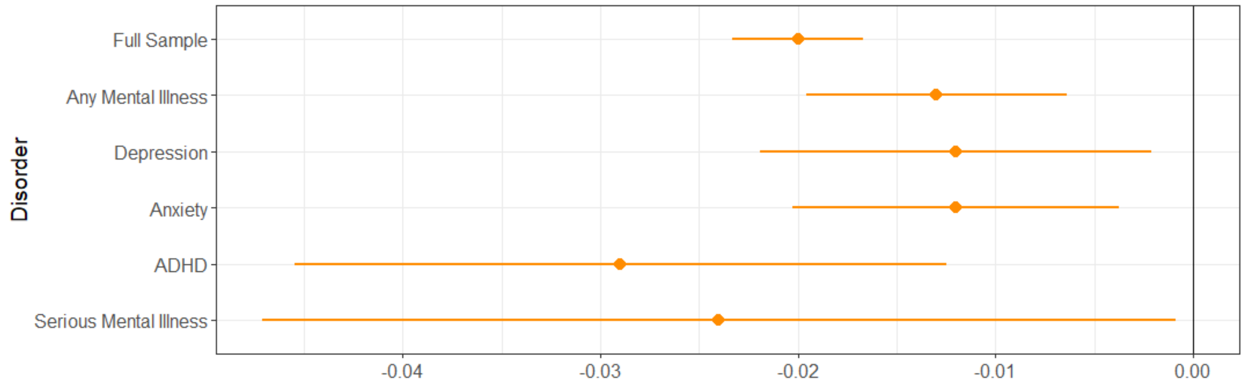
Notes: The points correspond to the coefficients in Table 7, with the whiskers representing the 90% confidence interval. See Table 7 for analytic notes.

Figure 8: Effects of using telemedicine on the probability of using emergency care



Notes: The points correspond to the coefficients in Table 8, with the whiskers representing the 90% confidence interval. See Table 8 for analytic notes.

Figure 9: Effects of shifting from in-person to telemedicine on overall spending (in logs)



Notes: The points correspond to the coefficients in Table 9, with the whiskers representing the 90% confidence interval. See Table 9 for analytic notes.

Appendix Table A1: Definitions of key measures

Measure	ICD-10 Diagnosis Codes	CPT-4 Procedure Codes	Other Inclusion Fields	Notes
Any mental health disorder	F2x-F6x, F80x-F83x, F84x (excl. F84.2–84.4), F9x	Psychotherapy: 90832, 90833, 90834, 90836, 90837, 90838, 90791, 90792, 90845, 90846, 90847, 90849, 90853	Any mental health specialist (specialty code): psychiatrist (15), clinical psychologist (61), licensed social worker (62)	Excludes disorders due to known physiological conditions, including mental retardation and Rett Syndrome. Up to 9 diagnosis codes are available per claim. Presence of an appropriate ICD-10 code in any of the 9 diagnosis codes qualifies a claim as an indicator for the respective disorder. Individual claims may indicate multiple disorders (e.g. DX1=F30, DX2=F40). In this case, the claim would get separate indicators for each individual disorder, but only a single indicator for 'Any mental health disorder.' The sum of claims indicating individual disorders need not equal the sum of claims for 'Any mental health disorder.'
Depression	F32x–39x, F92.0,			
Anxiety	F 40–48, F93, F94			
ADHD	F90x, 98.8			
Serious Mental Illness	F2x, F30x-F31x			

Telemedicine and telemental health	G0425, G0426, G0427, G0406, G0407, G0408, G0459, G2061, G2062, G2063, G0508, G0509, Q3014, T1014, 98970, 98971, 98972, 99421, 99423, 99441, 99442, 99443, 98966, 98967, 98969	Procedure Modifier Code = GT, GQ, 95; AMA Place of Service Code = 02	Telemedicine is defined as any claim that has at least one of the CPT-4, Procedure Modifier, or Place of Service codes listed. Up to 6 procedure and procedure modifier codes are available per claim (any one is valid to indicate telemedicine). A telemental health claim for disorder X is defined as a claim with both an indicator for X (see above) and an appropriate telemedicine indicator.
Psychotherapy	90832, 90833, 90834, 90836, 90837, 90838, 90791, 90792, 90845, 90846, 90847, 90849, 90853		
Psychotropic Medications		AHFS Pharmacologic-Therapeutic Classification System: 28.16.xx, 28.20.xx, 28.24.xx, 28.28.xx	