Estimating the Effects of Virtual Care Usage on Health, Care Utilization, Costs, and Racial Disparities

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Princeton University, Princeton, NJ	AB	06/2014	Economics
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After receiving my Bachelor's degree, I began working as a consultant for a boutique firm in Manhattan. This company (Kepler Group) appealed to me because it considered quantitative insights to being the key to its success with clients. I worked primarily with healthcare clients, both designing incentivized health care programs, and evaluating their clinical and economic effectiveness. Many of the programs we designed and often implemented contained technological foundations, either at the health system level (EHR changes or improved interoperability) or at the patient/consumer level (mobile and/or digital health, patient portals, etc.).

Being involved intimately with this work allowed me to see how technology and health care inextricably linked, and will only grow more clinically and economically linked over time. But even while these programs often saw successful rollout, I often witnessed how the treatment effects were generally strongest for those with higher baseline health and income, and were often not members of racial or ethnic minorities. This anecdotal evidence inspired me to re-enter academia to study these effects formally, both to understand underpinning causes and influence future policy and technologies. My long-term goals involved developing new technological advancements and testing how they affect health outcomes and health care costs. A particularly important sub-goal of this long-term goal is to research how these advancements impact health disparities and how future technology can reduce said inequities.

In addition to my academic and professional history, my current work exemplifies my commitment to becoming a better health economist. I have excelled in my graduate school coursework and seek out relevant coursework within my program, as well as in economics and data science. My interest in health-related technological advancements inspired me to join the Emergency Digital Health Innovation research team, led by Dr. Megan Ranney at Brown's Alpert Medical School. This opportunity allows me to stay abreast of advancements in the field of emergency medicine, a specialty ripe for innovative technology. Through this team, I also serve as a research assistant on a predictive analytics project that

implemented a model-derived EHR flag in the hospital system ED predicting likelihood for ED recidivism. Additionally, I have completed a fellowship with Pfizer, working with its Global Medical Impact Assessment team. I also completed an internship with the interoperability group at UnitedHealth Group, building predictive models using their Medicare Advantage data. Both of these experiences have been incredibly valuable, exposing me to how this type of research is conducted in different industry settings, complementing my work at Brown.

Over the course of my doctoral career at Brown, I published 5 peer reviewed articles with 4 others currently in review or accepted but not published. I also presented work at conferences for Health Services Research and Health Economics. As an instructor, I taught two classes. For undergraduates, I served as a teaching assistant for the United States health system course. For graduates, I helped teach a class on Medicare and analyzing Medicare claims. The culmination of these experiences helped me grow as a student and researcher, and I am grateful for everyone who helped me along this path.

PREFACE

Coming into graduate school, I was fascinated by health technology and how it was leveraged at the time (the summer of 2018). I was interested in the economics of wearable technology, and had begun to formulate the question of whether they work, and if so, for whom. Health inequity was top of mind as I begun to think through this question, as I created a hypothesis that wearables only benefit those healthy at baseline, while not being as useful for those with relatively worse health status. While I couldn't formulate it, this begun my interest in the "Digital Divide", a guiding concept for this dissertation's final chapter.

Upon arrival to Brown it became quickly apparent, as it does to many new doctoral students, that data may not be readily available to answer my research question. I remained interested in health IT, but begun to reconsider the ways in which I could operationalize this using available data. The moderate rise of virtual care interested me but, outside of behavioral health, it wasn't often leveraged outside of isolated clinical trials. This changed during the spring of my second year, with the onset of the global COVID-19 pandemic. I remember each minute of the 12-hour drive home from Providence to Chicago, stopping only for gas. While we were re-calibrating to learning, teaching, and researching remotely, millions of Americans began using telemedicine and patient portals to manage their health. It is hard to describe how it felt to learn, teach, and do public health in this moment, as I begun to see the importance of my research interests in real time.

Due to some incredible luck, I was able to find mentors who are leaders in their fields, and at the helm of administering and researching virtual care in multiple states. Their guidance helped me narrow my research question, and gave me access to data that could get at the questions that had fascinated me for years. Telemedicine and patient portal use has increased dramatically since March of 2020, and both appear to remain important components of patients' care management. Understanding the optimal use of these technologies involves finding out what types of care can be best administered virtually, and for whom it will most benefit. These are complex questions, and I count myself grateful to be in a position to contribute my research to such an important question.

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This work would not have been possible without contributions from so many friends, family and colleagues. First, to Ira Wilson, who served as one of my interviewers when applying to Brown, my academic adviser, and my dissertation chair.

Your kindness and passion to do good research inspired me to hold myself to the highest standard, and none of this work would have been possible without your guidance.

To my larger dissertation committee, thank you for helping me through this process. It made this whole process much less daunting, and I aspire to mentor others as you all have mentored me. To my fellow 2018 PhD cohort, I can't imagine beginning this journey with anyone else besides the seven of you. I think our interests and skills complemented one another's so well, and I can't wait to see what all of you accomplish in this field. To the other HSR PhD students, HSPP faculty, and staff, the collection of your expertise, intelligence, and kindness made an indelible impact on me. Brown was the absolute best place to pursue this degree, and everyone in this department contributes to this belief.

Another strength of Brown's program is in its devotion to interdisciplinary study. Much of my mentorship came from students and faculty outside of HSPP. To everyone at the Center for Digital Health, the Brown Center for Biomedical Informatics, Boston University School of Public Health, and the Rhode Island Quality Institute who helped me along this path, and contributed to my growth, thank you for helping to round out my training.

To my friends, from childhood, through Princeton and New York, culminating in Providence, you always provided a place to go to regain perspective. The PhD journey is naturally a solitary one, and it can become lonely really easily. Thank you for helping me never let it get there for me.

To Mom, Dad, Nat, Nana, Poppee, Grandmama, Granny, and all other family, thank you for giving me the love I needed to be fearless in this endeavor. Your support is ever-present, and I can never adequately express how important it is to me.

And to Stacey, you are undoubtedly the best thing to come from my PhD journey. Thank you for agreeing to spend life with me, and your love and support is all I need to get through life's highs and lows. You and Juno mean the world to me.

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While virtual care had been growing in capability and use in preceding years, the onset of COVID-19 greatly accelerated these trends. Telemedicine and patient portals possess the potential to improve care management but concerns persist as to their effectiveness as complements and substitutes to in-person care.

This dissertation uses data from Medicaid administrative claims, an Electronic Health Record, and a statewide Health Information Exchange (HIE) to understand how COVID-19 (and the ensuing rise in virtual care use), influenced care utilization, health status, care costs, and racial disparities in health and healthcare.

Chapter 1 uses administrative claims data from a large Massachusetts Medicaid ACO to understand how FQHC-level telemedicine use affects care engagement, costs, and health quality amongst Federally Qualified Health Center (FQHC) patients with multiple chronic conditions. Chapter 2 uses data from Rhode Island's HIE to investigate the relationship between patient-level patient portal usage and care engagement and health quality amongst Rhode Island patients. Given the inequities in virtual care access and use, disparities in outcomes may widen with increased overall adoption (an occurrence known as "The Digital Divide"). Thus, Chapter 3 uses both aforementioned datasets to understand how these policies differentially affect racial sub-groups. To investigate these relationships, this dissertation leverages a variety of econometric techniques including Difference-in-Differences (Chapters 1 & 2), and Triple Difference (Chapter 3) models. Ultimately, these chapters find that increased usage of these technologies led to increased care engagement while not negatively affecting health and direct health care costs. Further, equity-driven virtual care rollout did not widen racial disparities, but target initiatives may be required to ensure marginalized groups have equal access to these technologies.

While the emergent COVID-19 threat has lessened, virtual care has demonstrated staying power. Understanding the types of care that can be administered remotely is crucial for policymakers, payers, providers, and patients as they figure out virtual care's ongoing role in the US health landscape.

CHAPTER 1: Quantifying the Effects of Increased Telemedicine Availability on Utilization, Measure Quality, and Cost amongst Multimorbid Federally Qualified Health Center Patients

INTRODUCTION

Telemedicine, two-way synchronous virtual (video and audio) clinical services between patient and provider, has been used in its current form for approximately three decades (1). Telemedicine (and telehealth, a broader term inclusive of non-clinical services) has historically been more likely to be used by certain groups (younger patients, those with higher levels of internet access, and those with fewer barriers to receiving in-person care) (2). Even amongst patients from largely underserved backgrounds, telehealth use was more likely to be used by patients in rural areas and for those accessing mental health care (3). These differential levels of usage can be attributed to these structural and patient-level factors, but providers have also had an influence on telehealth adoption. Specifically, provider telehealth use is tied significantly to the ease and level of reimbursement linked to virtual visits (3). In the aggregate, lack of reimbursement, training, and resources limited telehealth adoption in its early years.

While voluntary uptake remained relatively low through the 2010s, researchers began conducting randomized control trials to assess the efficacy of virtual visits. These studies did not focus on determinants of usage but helped demonstrate efficacy in various situations. Many of these studies focused on patients with diabetes, and have tended to find a positive effect of telemedicine on various aspects of disease management, including "adherence to blood glucose monitoring, day-to-day decision-making related to self-care, and adherence with medications" (4). Conceptually, we believe that telemedicine leads to these outcome changes through the lowering of barriers traditionally associated with in-person care. In this framework, reducing transportation time and costs and allowing for more scheduling flexibility allows for patients to focus more on disease management and less on the administrative tasks that accompany in-person care. Further, given

the structural barriers imposed on marginalized populations that make these tasks more difficult to complete, the potential benefits should be even greater for underserved patients (provided both groups use the technology equally). The disparities in telehealth use, however, could contribute to a widening racial disparities in utilization, health, and costs (5-11). This worrying disparity in access to and use of technology has been referred to as the "digital divide", and has been studied as technological capabilities continue to advance in care delivery (6, 7, 12-15). Research has shown that key underserved populations (including Medicaid, low-income, and rural populations) experienced significantly lower telehealth usage (16). This appeared to change, however, with COVID-19 onset as virtual consultations became more necessary.

Over the period of 2020-2023, telemedicine usage increased considerably, spurred by the COVID-19 pandemic and aided by growing investments technological infrastructure and capabilities. Policies at the federal and state level continue to encourage these trends. For Medicaid specifically, this included expanding the population eligible to use telehealth, allowing for telehealth reimbursement to be covered at parity with in-person visits, expanding technological capacities via grant resources, training support, and technical assistance, and broadening provider types that are permitted to deliver virtual care (17). Increased pandemic telehealth access has been associated with increased primary care visits at a lower per-visit cost (18). Recent research in practice-level telehealth use, however, has shown mixed effects on quality of care measures (19-22). Given these trends, understanding how increased access and usage affects the health of marginalized populations and attributed expenditures is an important extension of the current knowledge base, particularly as federal payers consider how to continue reimbursing these services.

An important underserved population that hasn't received extensive attention in the literature, despite being positioned to potentially disproportionately benefit from telehealth, is low-income, multimorbid patients. People with multimorbidity possess at least 2 chronic conditions, and they constitute a growing proportion of US adults. As of 2018, 27% of adults had at least 2 chronic conditions (23). Further, amongst subgroups, those with public insurance and those living in rural areas constituted higher than average multimorbidity prevalence (23). This group also constitutes a significantly high-need and high-cost cohort, as prior research states that the cost and health effects of multimorbidity is multiplicative rather than additive (24, 25). Such a population could conceivably benefit from remote care, and could ostensibly provide valuable

cost savings. These patients are likely to be care high-utilizers, which bears significant costs and inconvenience. Any ability to move care virtually without harming health or costs may benefit patients, providers and payers.

This directly applies to the multimorbid cohort of patients diagnosed with Diabetes Mellitus, Hypertension, and Hyperlipidemia (DHH). Successful chronic condition management depends on medication adherence, health-conscious decisions, and communication with health care providers. Patients with DHH require numerous medications, frequent interactions with providers, and self-monitoring of clinical biomarkers to ensure they are within a healthy range. Telemedicine, in theory, addresses these issues in a low-touch environment. A considerable body of research analyses relationships between telemedicine access and usage for chronic disease patients on a variety of outcomes related to quality, costs, and patient/provider satisfaction. Focusing on Diabetes and Hypertension in particular, studies have found that telemedicine aids in disease management and satisfies patients and providers (4, 26-39). Further, during the COVID-19 pandemic, early research has shown telemedicine to be a sufficient replacement to in-person care for patients with chronic diseases (30, 40). While this research exists for patients with individual chronic conditions, telemedicine's effects of patients with multiple chronic conditions remains under-studied. This research aims to address these important questions.

The shift to telemedicine holds significant promise for Federally Qualified Health Center (FQHC) patients. FQHCs often serve typically-underserved patients, and serve as the nexus of care coordination. FQHC providers provided needed access to a variety of providers, benefitting patients with multiple chronic conditions. Improving patient engagement at the FQHC-level holds promise to improve care engagement across all providers. Further, while telemedicine access and determinants of use in FQHCs have been studied, understanding effects on downstream outcomes and costs is relatively sparse. Massachusetts (MA) offers a great research setting to fill in knowledge gaps. In 2019, only 8% of Federally Qualified Health Centers (FQHCs) in Massachusetts (MA) were using telemedicine to deliver primary care or chronic disease management services remotely to patients (41). The onset of the COVID-19 pandemic, however, necessitated that providers and patients embrace various remote care modalities, including telemedicine, to enable continued access to care. By the end of 2020, 100% of MA FQHCs delivered at least some primary care or chronic disease care virtually via

telemedicine. Our objective was to assess how FQHC-level telemedicine use affected quality of care and direct health care costs for low-income patients with DHH in MA.

Methods

Data

We used uses data from Community Care Cooperative (C3)—the largest FQHC-based Medicaid Accountable Care Organization (ACO) in the US, which implemented an innovative and equity-driven telemedicine delivery model during the COVID-19 pandemic (42). Using on grant funding and donations, C3 expanded telehealth activity by expanding access to hardware and software, covered IT support, and helped meet the increased telehealth demand from COVID onset onwards (42). As of 2021, C3 was comprised of 18 FQHCs. Collectively, these 18 centers serve over 400,000 patients in Massachusetts (150,000 of which are Medicaid beneficiaries), and are committed to addressing a full range of medical, behavioral, and social needs. Our dataset ranges from 2018 to 2021, containing both Electronic Health Record (EHR) data and Medicaid claims data. From these data, we observe detailed demographic information, health care utilization and attributed costs, and measures of health care quality at the patient/month level.

Sample

To be included in our study, we required that patients were attributed to one of 16 of the C3 FQHCs (as defined by the patient receiving the plurality of their care at a clinic). We further excluded patients without evidence of visiting the FQHC in the prior 24 months as of month *m*, even if otherwise attributed to the FQHC. Two FQHCs did not see significant virtual visit volume and had some data abnormalities and were thus excluded from these analyses. Further, we required each patient to have a diagnosis of diabetes, hypertension, and hyperlipidemia, as determined by claims-level diagnostic data (i.e. one inpatient claim or two or more other claims with a diagnosis). Finally, we required patients to be non-elderly adults (between 18-64 years old), with at least one in-person visit to a C3 FQHC in both the pre-period (March 2018 – February 2020) and the post-period (April 2020 – December 2021). We exclude March of 2020 because this month, as this was where COVID cases began to increase dramatically, and health systems spent the month transitioning to virtual care. To ensure that insurance coverage is consistent throughout the sample, only months when the patient was enrolled in Medicaid (i.e. MassHealth) were included.

Treatment Definition

While all FQHCs in C3 operate under their equity-driven framework, each center transitioned to virtual care to varying degrees. For this research, we used the exogenous variation that comes with different FQHCs telemedicine adoption levels after March of 2020. To define treatment, we examined the proportion of medical care visits delivered by telemedicine after COVID-19 onset (i.e. from April 2020 – December 2021) at each FQHC. We grouped FQHCs into three distinct categories, low telemedicine (LT) (29-34% of all visits delivered via telemedicine, mean=32.8%), medium telemedicine (MT) (42-57% of all visits delivered via telemedicine, mean=51%), and high telemedicine (HT) (73-75% of all visits delivered via telemedicine, mean=73.8%). Patients were then assigned to a treatment group based on the FQHC to which they were attributed. In other words, treatment assignment was made at the FQHC level, rather than the patient level. This minimizes the role of patient selection into telehealth versus in-person care, where the availability of telehealth at an FQHC is predictive of a patient's likelihood of using telehealth but does not affect their selection of that FQHC as their place of care (as FQHC attribution was done prior to telehealth implementation). Telemedicine visits are defined via place of service and Current Procedural Terminology codes, with the exact definition listed in the appendix (Table 1.A1)

Outcomes

Our primary outcomes included care utilization and cost. Utilization outcomes included number of FQHC visits (in-person and total). Additional utilization outcomes included outpatient visits (non-FQHC and total), inpatient admissions, and emergency department (ED) visits (excluding those that resulted in inpatient admission). We also examined costs (based on allowed amounts), which included inpatient costs, ED costs, outpatient costs, and total costs.

Our secondary outcomes included measures related to recorded lab and vital data on monthly HbA1c and blood pressure values (systolic and diastolic). For all lab values, we used the minimum monthly values to best model valid lab results, excluding invalid measurements. Additional secondary outcomes focus on quality outcomes, specifically three Healthcare Effectiveness Data and Information Set (HEDIS) measures. These measures are binary outcomes, identifying whether a patient has had an annual retinal exam, demonstrated good blood pressure control (BP<140/90 mm Hg), and demonstrated poor blood glucose control (HbA1c>9.0%).

Statistical Analysis

The unit of analysis was the patient month. To estimate the causal effects of FQHC-level telemedicine use, we use a difference-in-differences approach with linear models to examine changes in patient-level outcomes for patients with LT vs. MT or HT telemedicine usage before versus after rapid implementation of telemedicine. The strength of this design allows us to analyze treatment groups of different composition, provided the data satisfies the appropriate assumptions. Thus, even if FQHCs differ in their demographics, the validity of effect estimates remain. Binary outcomes use linear probability specifications, while non-binary outcomes use ordinary least squares specifications. The general functional form of these models is depicted below in equation (1), estimating outcome *Y* for individual *i* in month *m* attributed to FQHC *f*:

$$(1) \qquad Y_{imf} = \beta_0 + \beta_1 Post_m + \beta_2 TeleFQHC_f + \beta_3 Post_m TeleFQHC_f + \beta_4 X_i + \propto_m + \delta_f + \varepsilon_i$$

$Post_j$ represents an observation occurring either before or after rapid implementation. $TeleFQHC_k$ represents whether the observation is LT, MT, or HT-attributed patient. The parameter of interest (β_3) is an interaction between *Post* and *TeleFQHC*, or our difference-in-difference. This tells us the effect of being a patient of a MT or HT FQHC (compared to a LT FQHC) after COVID-19 onset on a patient's health, care utilization, or cost paid by Medicaid. Additionally, models adjust for a patient-level covariate vector (X_i), applied month ($\propto_m$) and FQHC (δ_f) fixed effects, and used robust variance estimators. The covariate vector includes patient age, sex, race/ethnicity, preferred language, patient 5-digit zip code, and presence of one of 10 chronic conditions. Once a patient sees a diagnosis of a chronic condition, they maintain that diagnosis through the remainder of their observations. These types of models rely on the parallel-tends assumption, which requires that outcome trends of treatment and control groups must follow the same trajectory in the absence of treatment. To test this, we graphically depict unadjusted outcome figures to illustrate these trends and statistically model their differences. Additional assumptions rely on consistency, exogeneity, and positivity (43). There is no reason to suggest that observed treatment differs from counterfactual treatment, suggesting the consistency assumption is satisfied. Baseline levels of outcomes did not determine treatment assignment, suggesting the exogeniety assumption is satisfied. Each

FQHC had near-identical resources to incorporate telemedicine into their practices, suggesting the positivity mechanism is satisfied.

Results

Table 1.1 displays our sample's demographics by treatment category. After applying our inclusion and exclusion criteria, our sample included 94,581 observations from 2,433 beneficiaries. These observations come from 16 FQHCs, which are separated into LT (3 FQHCs), MT (11 FQHCs), and HT (2 FQHCs). Approximately 85% of all patient-months are from patients attributed to a MT FQHC. Approximately 10% of patient-months are from patients attributed to a LT FQHC, with 5% of patient-months attributed to a HT FQHC. Age is relatively consistent across treatment groups. In terms of sex, the HT group is more likely to be Male than the MT and LT groups. The MT group is less likely to be White (Non-Hispanic) and declare English as their primary language than both LT and HT groups. While most chronic condition flags were relatively consistent across groups, some (including COPD and MI) see more pronounced differences between treatment groups. As a whole, These patients, identified as having at least 3 chronic conditions (DHH), also have elevated incidence of other common chronic conditions compared to national estimates (44). We also conduct Pearson chi-squared tests with each categorical variable to determine that there is significant relationships between each variable and their attributed treatment group. From this, we determine that the categorical variables are significantly associated with treatment group at the 95% level. To see these patient demographics in aggregate, please refer to Table 1.A2 in the appendix.

Figure 1.1 illustrates how the primary modality of FQHC visits changes throughout the sample period. Up until March of 2020, there wasn't any significant telemedicine use. This changes dramatically, when in-person visits drop severely (illustrate by the lines) as telemedicine visits (the dots) quickly become the primary modality. This persists for about a year, until in-person visits become the more common modality in early 2021. The spike in in-person visits around this time is likely attributed to COVID vaccine's being made widely available during these months. Ultimately, the total number of visits (the bars) ultimately don't see a drop-off due to telemedicine's emergence.

Figure 1.2 focuses on Total FQHC visits by treatment group. The months prior to COVID-19 onset show total visit volume being largely consistent between the three treatment groups. As the treatment group classification indicates, these diverge pretty sharply in March 2020. HT FQHCs see more total visits in the pandemic's early months, as telemedicine

becomes the primary modality in each treatment group. The three treatment groups appear to converge in March 2021. For a FQHC-level breakdown of telemedicine visit proportion and treatment group categorization, please see Figure 1.A1 and Table 1.A3 in the appendix. Further, to see Figure 2 depicted as a function of telemedicine visits, and in-person visits, please see Figure 1.A2. Here we observe that each group takes a different amount of time to see in-person visits return to the primary modality. This took approximately a year for MT FQHCs and 5 months for LT FQHCs. HT FQHCs saw telemedicine visits remain as the primary modality for the entire post-pandemic period.

As previously mentioned, appropriate use of difference-in-differences methodology depends on how well the data satisfies the parallel trends assumption. To show that this is not a concern, we present three additional sets of adjusted outcome figures. Figures 1.3a-1.3f display outcome trends for our other utilization outcomes (aside from the FQHC visits described in the previous paragraph. Figures 1.4a-1.4e display trends for our cost outcomes. Figures 1.5a-1.5c display clinical biomarker outcomes, and Figures 1.6a-1.6c display HEDIS measure outcomes. While LT and HT outcome (blue and red lines, respectively) trends are more volatile due to sample size differences, they do move in concert with MT outcome (green line) trends. To further confirm this assumption, we estimate pre-trends and report the coefficients in Table 1.A4. We confirm these groups follow consistent trends for the entire sample period except for one (HEDIS: Retina, LT vs. MT). Interpretation of potential causal estimate will include this caveat.

An additional caveat pertains to the FQHC total visit/in-person visit pre-trends. When using the entire sample period, we do find that these treatment groups follow slightly different trajectories. Further investigation proves that this is due to the first months of the data, which seem to diverge after approximately 9 months in Figure 2. When removing the first months from pre-trends models we find parallel trends. Further, running the difference-in-differences estimates with the full dataset and with the first 9 months excluded yield near-identical estimates. Thus, given these additional checks, we can confirm that FQHC assumptions are also valid, despite the trends seen in the early months of our sample.

To view the model estimates for our coefficients of interest. Please see Tables 3-5. Unless otherwise stated, statistical significance is determined at the 95% level. Table 1.3 shows the coefficients of interest for the utilization outcomes. We see that after pandemic onset, HT patients see 0.25 fewer monthly in-person FQHC visits (CI: [-0.40,-0.09], p-value=0.002) than LT patients. LT patients see 0.06 fewer monthly in-person FQHC visits at the 90% level (CI: [-0.12,-0.002], p-value: 0.089). Despite fewer in person visits, both MT and HT patients see increased overall FQHC engagement

by 0.14 (CI: [0.07, 0.20], p-value < 0.001) and 0.16 (90% significance, CI: [0.02, 0.30], p-value=0.054) monthly visits, respectively.

Table 1.4 shows the coefficients of interest for the cost outcomes. We see that most cost estimates see no significant differences across most models, with the exception of ED costs and other costs. HT patients see $324 lower monthly ED costs than LT patients (CI: [-572,-75.6], p-value=0.01). HT patients also see $519 lower costs attributed to professional outpatient care than LT patients (CI: [-990,-48.6], p-value=0.03).

Table 1.5 shows the coefficients of interest for the biomarker and HEDIS outcomes. We observe that HT patients see a 0.96-unit increase in diastolic BP compared to LT patients (CI: [0.11,1.82], p-value=0.03). Both MT and HT patients see a lower probability of having controlled blood pressure than LT patients (4% (CI: [-0.07,-0.001], p-value=0.09) and 7% (CI: [-0.13,-0004], p-value=0.098), respectively) than LT patients at the 90% levels.

Discussion

These results collectively suggest that the higher levels of telemedicine adoption after COVID improved care engagement while not harming patients with DHH. Further, patient health amongst FQHC patients with DHH did not seem to significantly change based upon their attributed FQHC. While telemedicine has held promise for patients with chronic conditions in randomized control trials, research on its effects in observational studies had been scarce (45). With the pandemic creating the need for more virtual care, studies began to assess telemedicine's effect in real-world settings. This research analyses the telemedicine use patterns of 16 Massachusetts FQHCs, serving high-need and underserved patients across the state.

These FQHCs all belong to a state-wide Medicaid ACO, with a goal of improving health equity across Massachusetts. Our sample of people with DHH require active care management and routine patient/provider interaction. Thus, it is important to understand if those with a higher proportion of their care served virtually see differential levels of care engagement, health status, and attributed health care expenditures.

FQHC visits transition from exclusively in-person to being largely virtual in March of 2020, which persisted for about a year. Considerable heterogeneity existed, however, in the level of adoption across centers. Perhaps unsurprisingly, those with a higher proportion of visits served virtually see telemedicine as the dominant visit modality for longer than other

FQHCs. Relatedly, it is important to understand whether visit volume is significantly different across treatment groups after pandemic onset. Since HT patients are estimated to have -0.25 fewer monthly in-person visits than LT patients, we can reasonably infer that HT patients were substituting some in-person visits with virtual visits. When looking at total visits, however, we do see that MT and HT patients (at the 90% level) observe higher monthly FQHC visits than LT patients. Ultimately it does seem like being a patient of a FQHC with a higher proportion of telemedicine use leads to improved FQHC care engagement, especially in the earlier months of the pandemic.

When focusing on other forms of health care utilization, we do see that there doesn't appear to be significant differences in adverse health events and corresponding utilization. Importantly, inpatient and emergency utilization are unchanged across treatment groups. Some of the primary concerns related to the emergence of telemedicine have been related to the level and intensity of care that may be leading to adverse events (22, 45-48). While more long-run effects of this shift may yield different conclusions, the 18 months following COVID onset did not see differential levels of adverse health events between the low and medium/high telemedicine FQHCs. Such findings support the assertion that needed shifts to virtual care do not necessarily influence adverse health events. Further, even without the need to shift care virtually due to a public health emergency, these results suggest that telemedicine is a viable alternative to in-person care for certain types of visits.

With the increase in telemedicine use, research into its effects on health care costs for patients, providers, and payers is needed (26, 28, 46, 49, 50). While each coefficient of interest is negative, only two of which are significant. These models suggest that monthly ED costs and professional outpatient costs are lower for HT FQHC patients than LT FQHC patients. From a patient/payer perspective, this is promising as it suggests that if care needs to be transitioned to telemedicine, there will not be utilization-related cost increases, and there may even be cost savings. This is in addition to reductions in transportation costs and lost wages that may result from taking off work during business hours to receive in-person care. Future iterations of this research should prioritize factoring in these indirect costs, as well as the costs of scaling up telemedicine use (including increased internet connectivity, purchased devices, and training). Similarly, including certain costs borne by providers would also be valuable, including the costs of using these technologies, and the reimbursement involved with training providers.

Within this cohort with multimorbid patients, estimating clinical biomarker measurements helps us understand how higher telemedicine use influences daily patient health status. We observed that MT patients see a 1-unit increase in diastolic

blood pressure over LT patients which, while statistically significant, is unlikely to be clinically significant. Each other coefficient of interest being statistically insignificant suggests that daily health status is largely unaffected by receiving a larger share of FQHC care via telemedicine. Within a high-need cohort that can strongly benefit from virtual care, this is a promising finding for those looking to manage chronic conditions.

Similarly, HEDIS measures offer the ability to estimate the performance of these FQHCs, as well as how that performance affects patient health. While none of the coefficients of interest are significant at a 95% level, being a MT/HT patient corresponds with a lower probability of having controlled blood pressure (compared to a LT patient) at a 90% level. While these estimates are concerning for FQHCs that adopt telemedicine, this may be due to HT patients being less likely to have documented measurements due to their increased virtual health care utilization. Unless they had some type of remote patient monitoring capability, the absence of a reading can be marked as not satisfying the criteria. Thus, the HEDIS models may not be accurately capturing health status. Coupled with the biomarker models, HEDIS estimates suggest that chronic disease management is not affected by increased telemedicine use.

This research extends the current knowledge base in a couple ways. Previous research has found that primary care practices with high telehealth use observed higher rates of ambulatory care-sensitive conditions than low-use practices (22). Such studies focus on the beginnings of the shift to virtual care, and does not focus on an underserved patient population covered by public insurance. Such a population stands to especially experience telemedicine's benefits, as it theoretically lowers cost, logistical, and transportation barriers to care for those with chronic conditions (51). Thus, our findings extend previous research to a new cohort with an extended outcome window. Further, this research fills a stated need for more research into the effect of telemedicine on health outcomes (10, 26, 45, 46, 51, 52). We extend this research further in chapter 3, as we analyze how these different levels of FQHC-level telemedicine use influence racial disparities in these outcomes.

Such research provides valuable policy implications. Although COVID is formally no longer recognized as a public health emergency, health systems need to learn how to integrate appropriate telemedicine into routine care. Understanding the benefits (or lack of downsides) of telemedicine is crucial to the continued development of virtual care infrastructure. The past few years have shown that a significant proportion of patients were satisfied with virtual care and see use for it going forward (53, 54). Although many patients may prefer in-person care as a primary option, there is demonstrated benefit to offering virtual care, and this research supports this from a care engagement and quality perspective (54). Patients will

likely prefer in-person visits to virtual visits for certain care (yearly physicals, for example), but virtual care may be more desirable for more informal check-ups. As most outcomes do not appear to significantly change, types of visits that are preferred virtually should be encouraged and used more. Regardless of the availability of in-person visits, if patients prefer virtual care that doesn't negatively affect health, it should be made accessible. Further, the results of our cost-related models provide important evidence that increased telemedicine use did not contribute to care-related cost increases. While further research on additional cost outcomes is warranted to get the full picture from a cost-effectiveness perspective, this research helps inform the funding needs for these types of care pathways.

Despite this, there are limitations to this work. First, natural segmentation of the three treatment groups led to the MT group having a significant majority of observations. While this doesn't limit the research from observing certain significant results, having more LT and HT observations would help to quantify the true effect estimate. As telemedicine use continues to comprise a significant portion of claims, analyses on these topics will have more available data. Second, certain outcomes, particularly those related to clinical biomarkers, had fewer observations than the full dataset. A larger body of data may yield significant estimates, supporting the need for future research on long-run outcomes related to HbA1c and blood pressure management amongst high-need patients with Diabetes and Hypertension. Third, there may have been unobserved confounding that affected both FQHC-level telemedicine uptake and patient-level outcomes, leading to biased estimates. While certain provider-level characteristics may lead to such confounding, there isn't reason to believe that the composition of physicians at each FQHC differ in a way that would lead to this bias. Fourth, these data only cover 2018-2021. More recent data will provide valuable insight on the lasting effects of these changes. Finally, while this is a comprehensive data set, it only captures information from one state's ACO which could potentially limit external validity.

Taken together, however, this research provides evidence supporting continued use of telemedicine for applicable types of care going forward.

Conclusion

Within a health equity-driven Medicaid ACO in Massachusetts, higher FQHC-level telemedicine uptake after COVID-19 onset led to more care engagement, potentially lower health care costs, and unchanged health status among DHH patients. Such results suggest that telemedicine may be beneficial to patients with multimorbidity who experience barriers related

to in-person care. While many types of care require in-person visits, understanding how and when to use virtual care will warrant research.

Tables and Figures

Table 1.1: Demographics across Treatment Category

Demographic	**Low (n=10,084)**	**Medium (n =80,172)**	**High (n =4,325)**
Mean Age (SD) *	52.2 (8.2)	54 (7.8)	52.2 (9)
Sex, N (%) *			
Female	5,225 (51.8)	42,845 (53.4)	1,193 (27.6)
Male	4,859 (48.2)	37,327 (46.6)	3,132 (72.4)
Race, N (%) *			
White, NH	5,370 (53.3)	20,709 (25.8)	2,272 (52.5)
Black, NH	455 (4.5)	13,940 (17.4)	668 (15.5)
Hispanic, any race	4,016 (39.8)	40,657 (50.7)	1,075 (24.9)
Asian or PI, NH	58 (0.6)	2,328 (2.9)	192 (4.4)
Other race	117 (1.2)	766 (1)	72 (1.7)
>1 race	36 (0.4)	770 (1)	0 (0)
Unknown	32 (0.3)	1,002 (1.3)	46 (1.1)
Primary Language, N (%)*			
English	5,783 (57.4)	30,778 (38.4)	2,478 (57.3)
Spanish	1,953 (19.4)	28,368 (35.4)	593 (13.7)
Other Language	0	46 (0.06)	0
Unknown	2,348 (23.3)	20,980 (26.2)	1,254 (29)
Condition, N (%) *			
Mental Health History	8,096 (80.3)	60,417 (75.4)	3,356 (77.6)
Substance Use History	5,168 (51.3)	35,226 (43.9)	2,194 (50.7)
Asthma	3,154 (31.3)	26,222 (32.7)	1,080 (25)

Chronic Obstructive Pulmonary Disease	3,002 (29.8)	19,924 (24.9)	556 (12.9)
Cardiovascular Disease	3,685 (36.5)	29,255 (36.5)	1,540 (35.6)
Ischemic Heart Disease	2,814 (27.9)	21,219 (26.5)	1,191 (27.5)
Myocardial Infarction	500 (5)	6,266 (7.8)	422 (9.8)
Atrial Fibrillation	575 (5.7)	5,115 (6.4)	353 (8.2)
Cerebral Vascular Incident	831 (8.2)	8,139 (10.2)	266 (6.2)
Heart Failure	1,162 (11.5)	10,419 (13)	569 (13.2)

*= Categorical Variables are significantly associated with FQHC Treatment Group

Figure 1.1: FQHC Visit Trends, by Sex and Modality

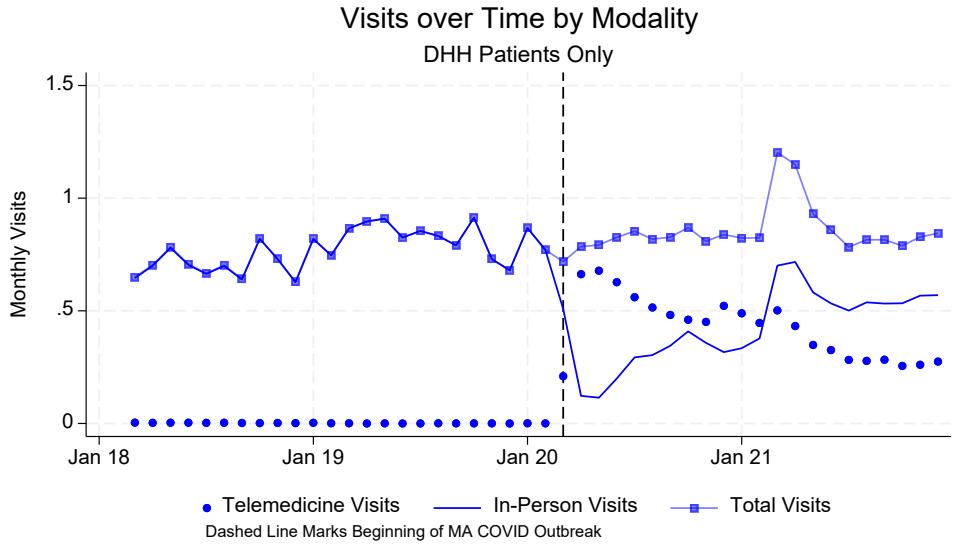
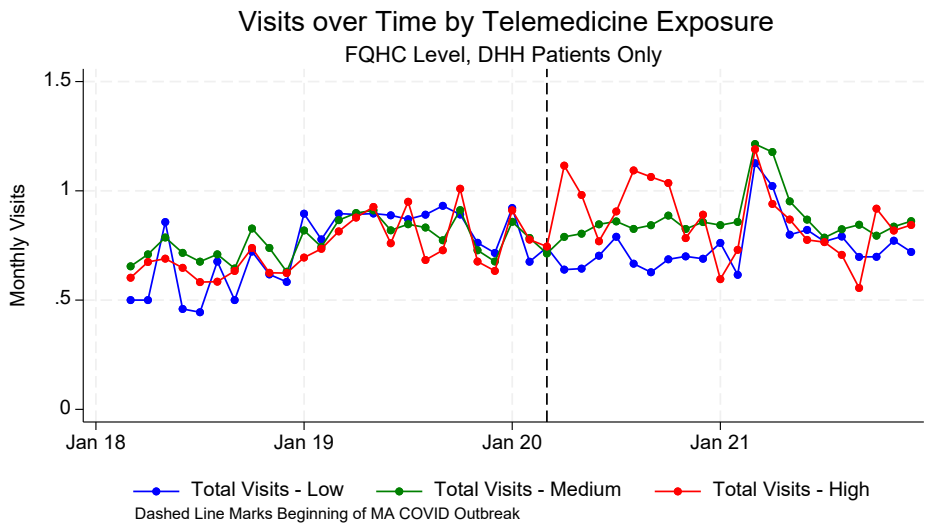
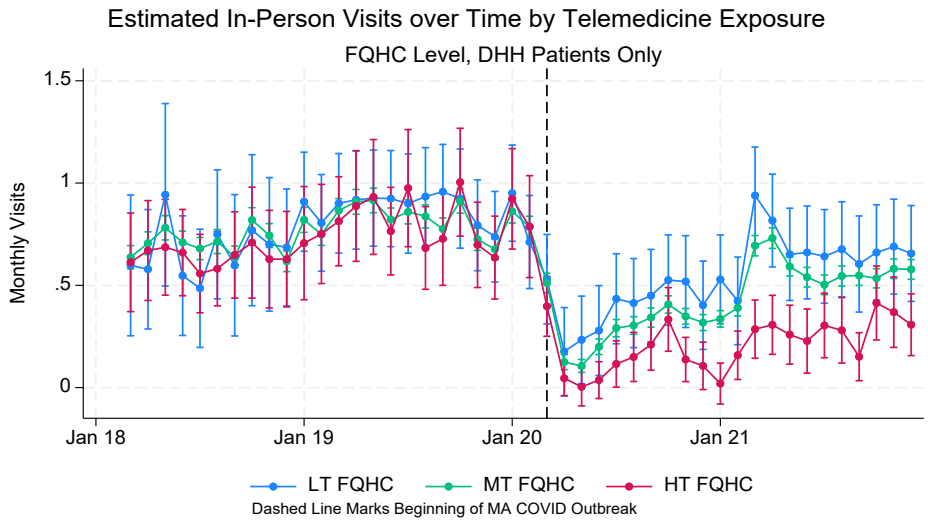


Figure 1.2: FQHC Total Visit Trends, by Treatment Group

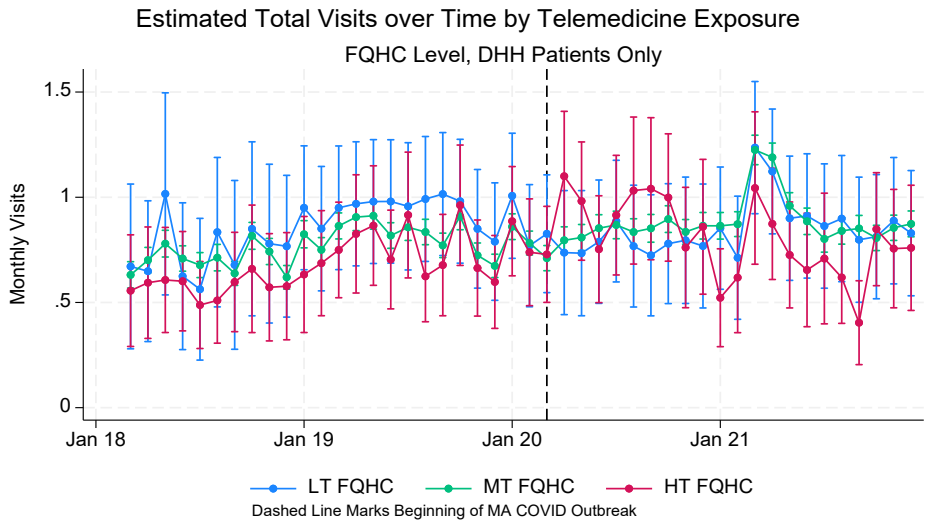


[Figures 1.3a-1.3f](): Adjusted Utilization Trends

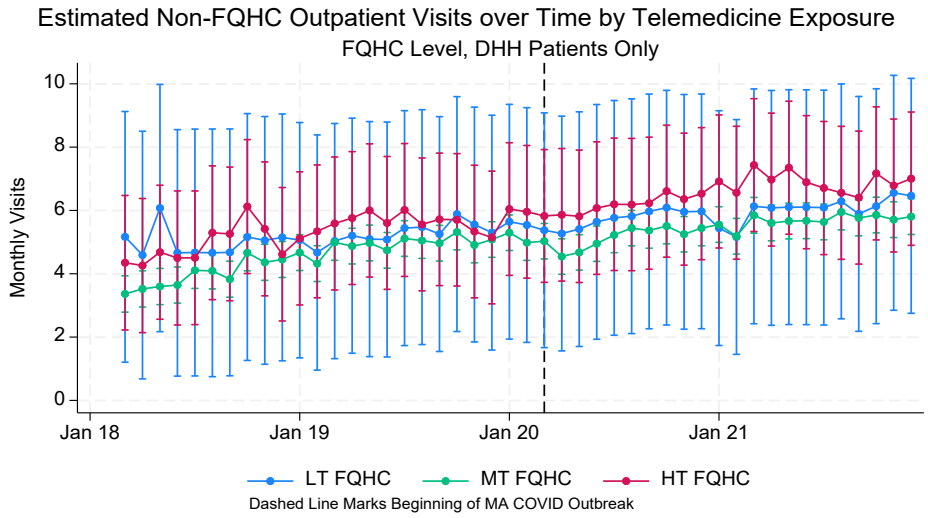
3a: FQHC In-Person Visits



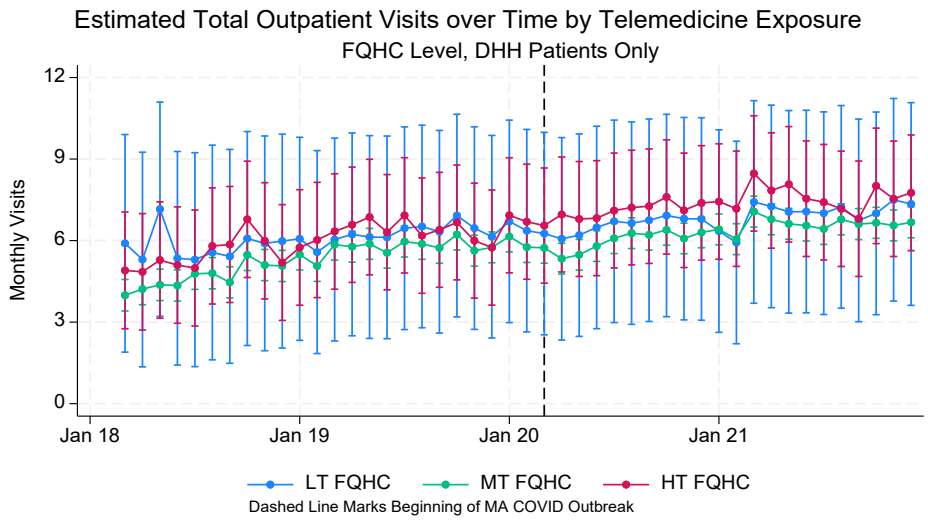
3b. FQHC Total Visits



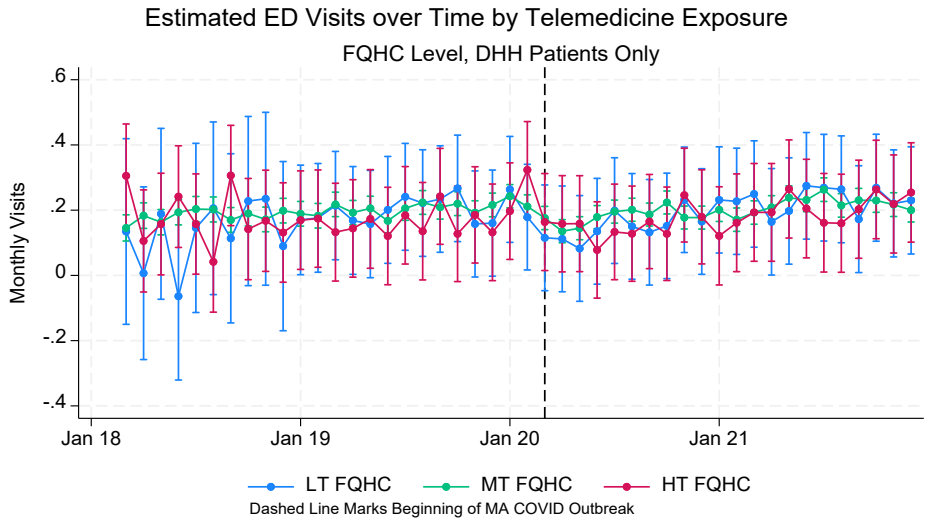
3c. Non-FQHC Outpatient Visits



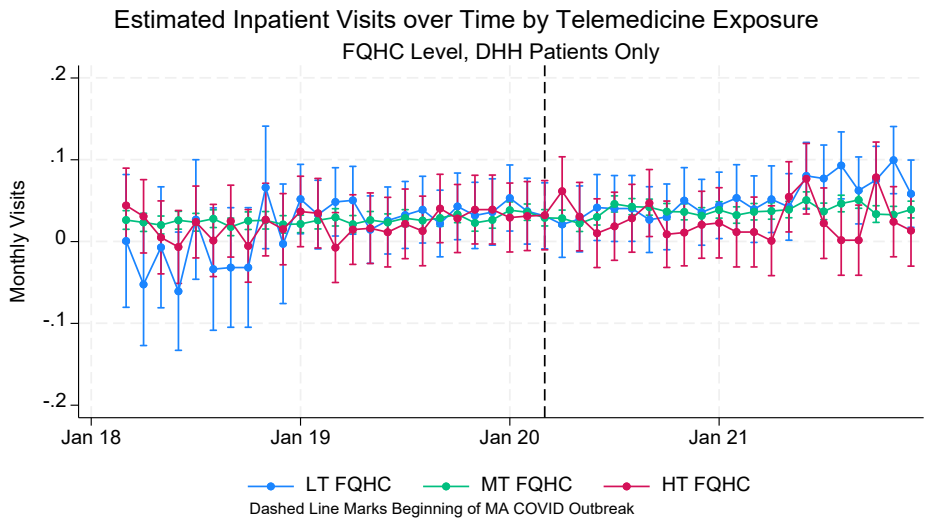
3d: Total Outpatient Visits



3e: Emergency Visits

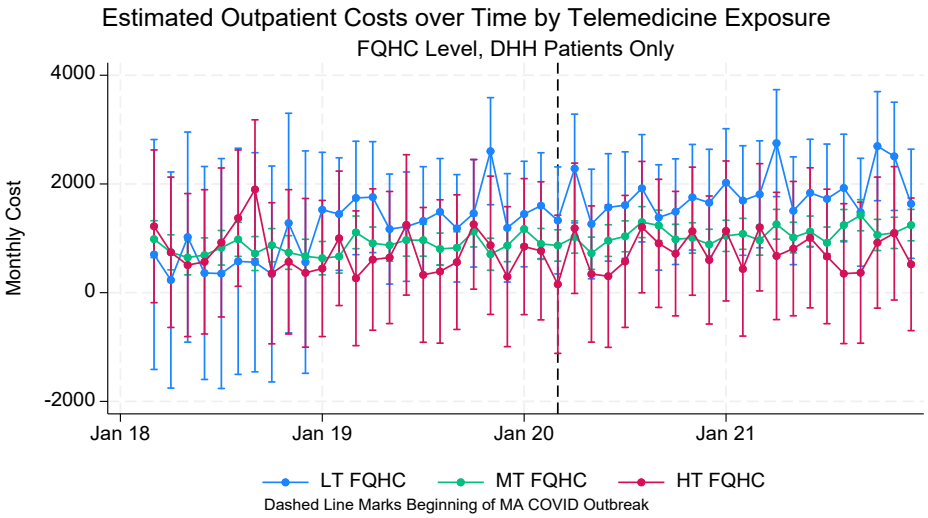


3f: Inpatient Visits

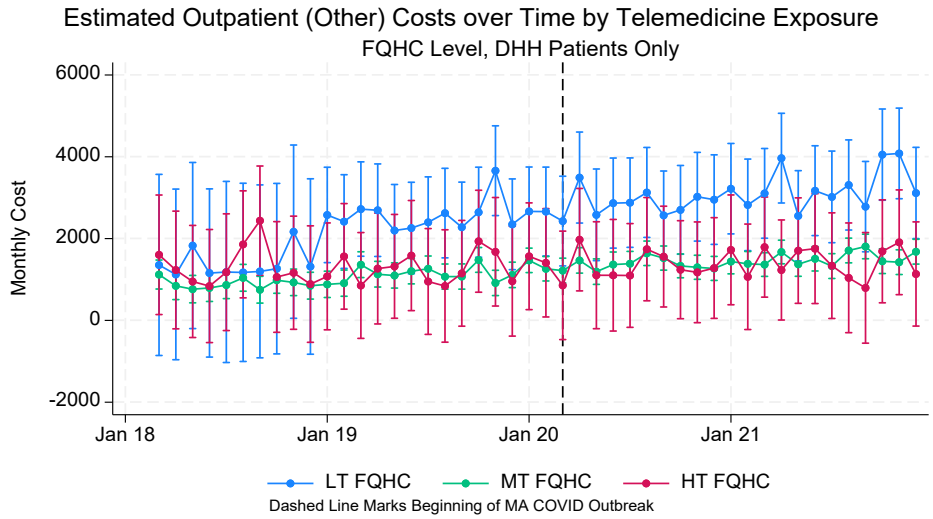


[Figures 1.4a-1.4e](): Cost Trends

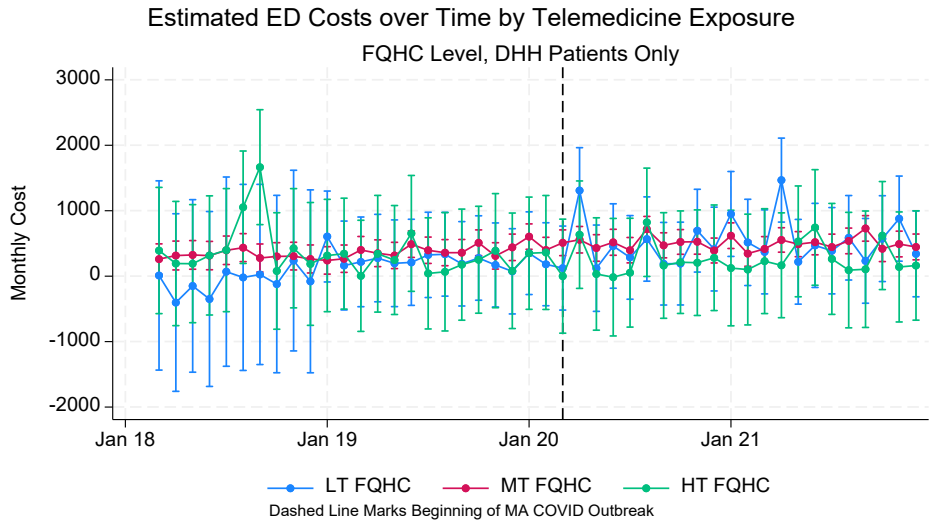
4a: Outpatient Costs



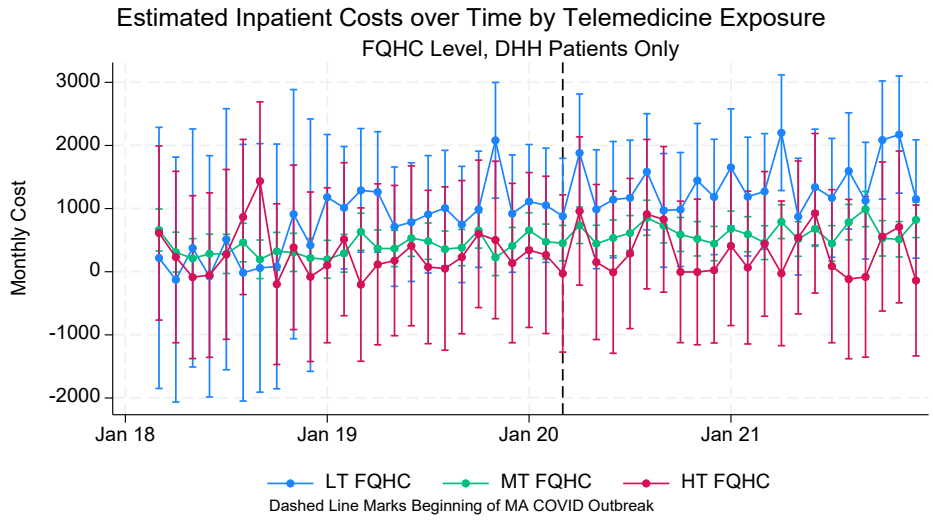
4b: Other Professional Outpatient Costs:



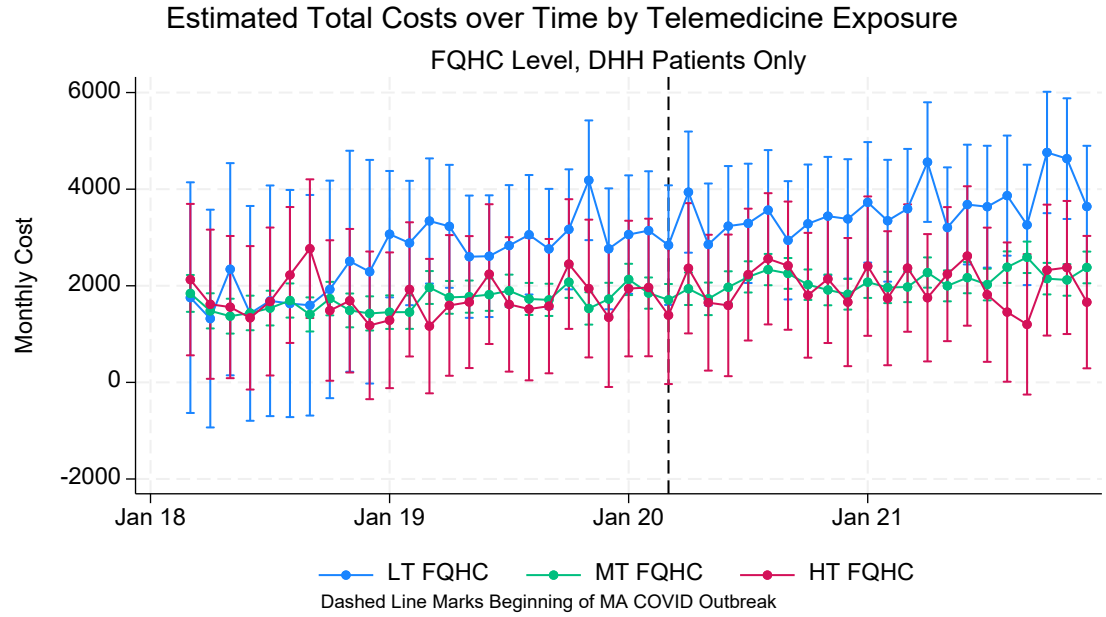
4c: Emergency Department Costs



4d: Inpatient Costs

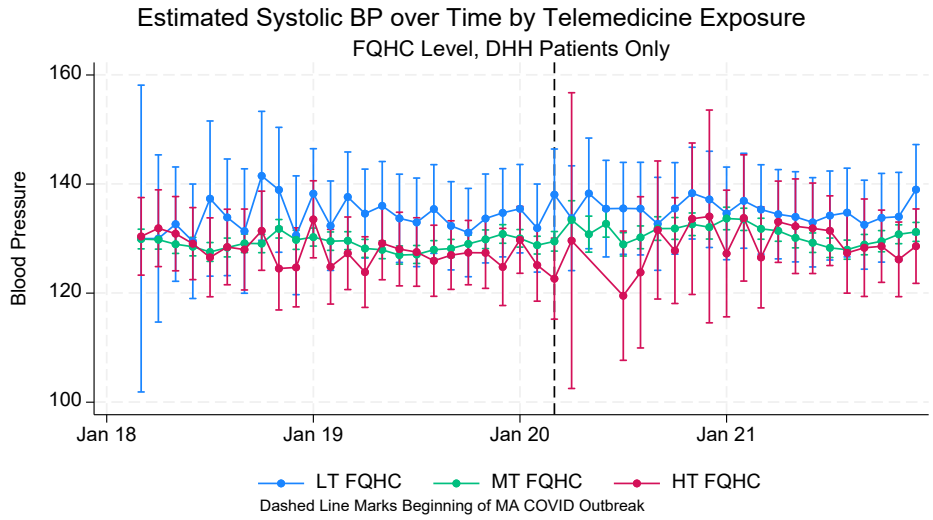


4e: Total Costs

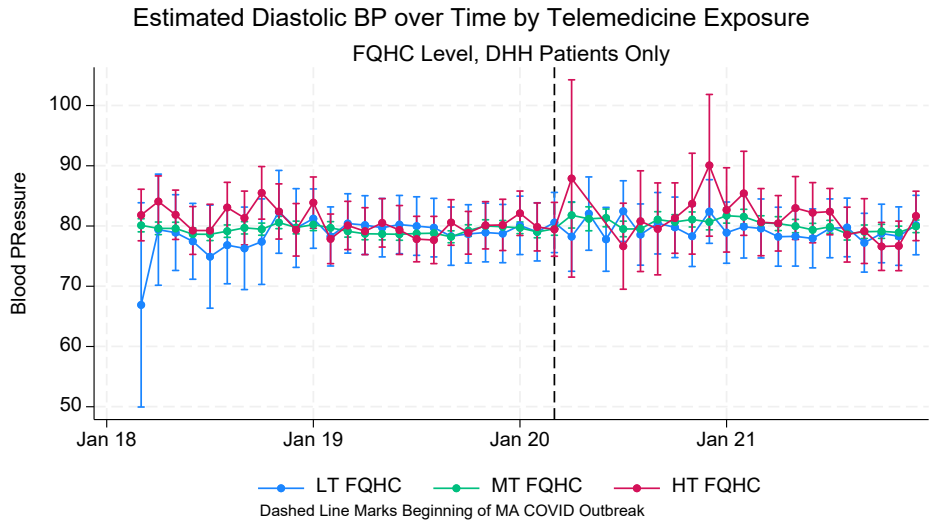


Figures 1.5a-1.5c: Biomarker Trends

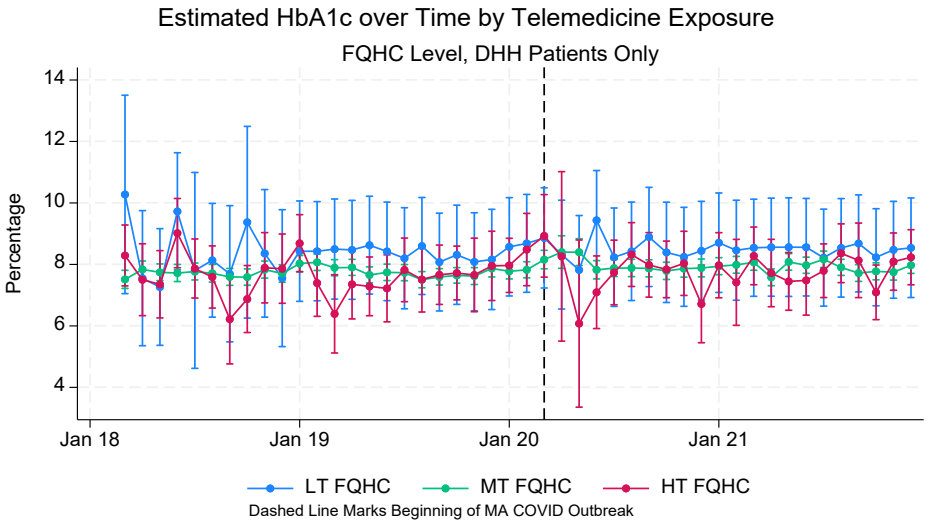
5a: Systolic BP



5b: Diastolic BP

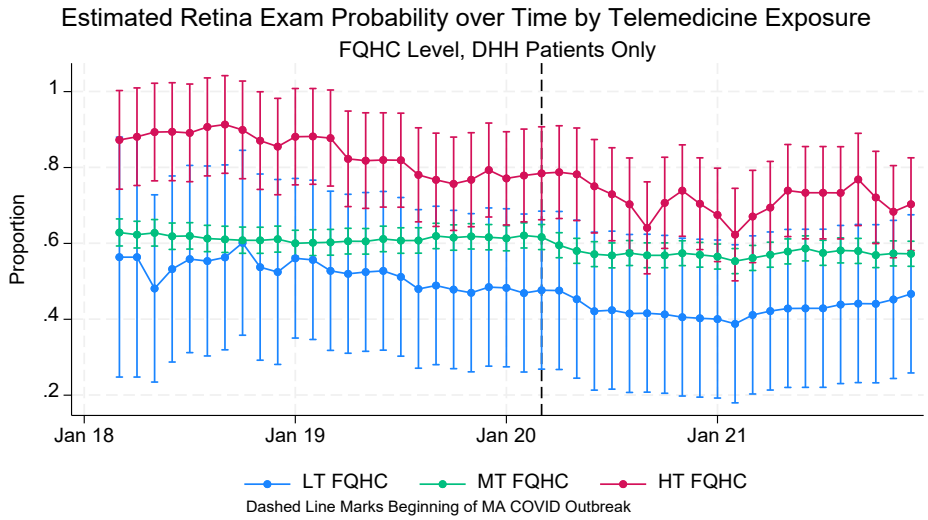


5c: HbA1c

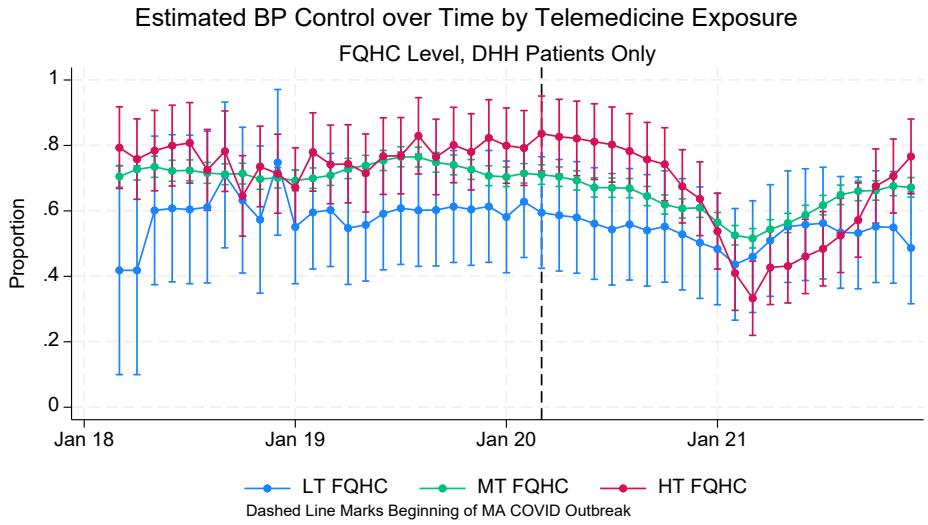


Figures 1.6a-1.6c: HEDIS Trends

6a: Annual Retina Exam



6b: Blood Pressure Control



6c: Poor HbA1c Control

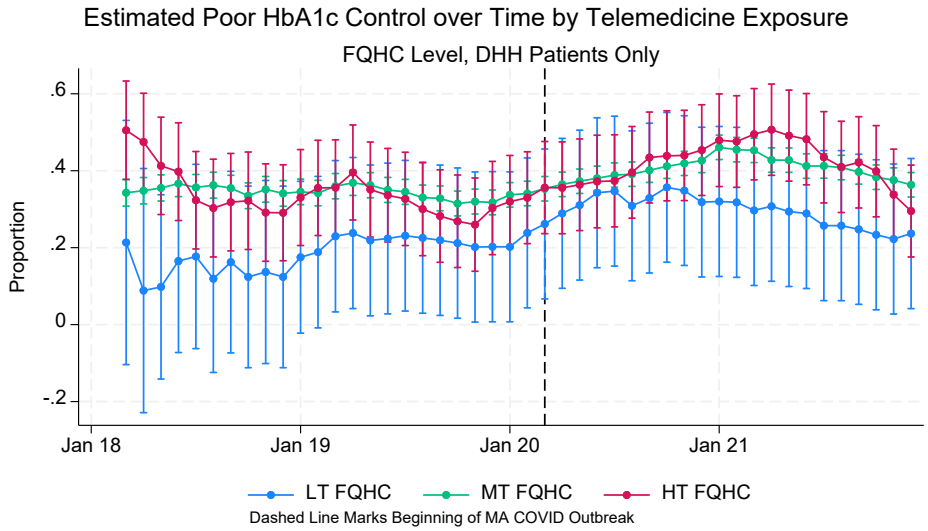


Table 1.3: Utilization Regression Coefficients of Interest

		LT		MT		HT		LT:MT			LT:HT		
	N	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DiD	95% CI, p-value	Unadjusted DiD	Adjusted DiD	95% CI, p-value
FQHC In-Person	*94,581*	0.83	0.5	0.77	0.43	0.74	0.23	-0.01	**-0.06***	(-0.13,0.009), 0.089	-0.18	**-0.25****	(-0.40,-0.09), 0.002
FQHC Total	*94,581*	0.83	0.75	0.78	0.87	0.74	0.87	0.17	**0.14****	(0.07, 0.20), <0.001	0.21	**0.16***	(-0.003,0.32), 0.054
Outpatient (non-FQHC)	*94,581*	4.56	4.98	5.2	5.79	3.41	4.63	0.17	**-0.04**	(-0.47,0.38), 0.842	0.80	**0.3**	(-0.44,1.04), 0.430
Outpatient (Total)	*94,581*	5.39	5.73	5.98	6.66	4.15	5.5	0.34	**0.09**	(-0.34, 0.53), 0.667	1.01	**0.46**	(-0.3,1.22), 0.236
Inpatient	*94,581*	0.033	0.042	0.025	0.034	0.03	0.035	0.00	**-0.008**	(-0.026,0.01), 0.385	-0.004	**-0.01**	(-0.036,0.01), 0.265
ED	*94,581*	0.19	0.16	0.19	0.19	0.19	0.2	0.03	**0.001**	(-0.038,0.04), 0.95	0.04	**0.0004**	(-0.062,0.063), 0.99

**= Significant at 95% level, *=Significant at 90% level

Table 1.4: Cost Regression Coefficients of Interest

		LT		MT		HT		LT:MT			LT:HT		
	N	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DiD	95% CI, p-value	Unadjusted DiD	Adjusted DiD	95% CI, p-value
Outpatient Costs	*76967*	892	1144	952	1088	839	787	-116	**-172**	(-564,219), 0.387	-304	**-313**	(-763,138), 0.173
Outpatient (professional) Costs	*76967*	1271	1706	1311	1628	1284	1272	-118	**-247**	(-673,179), 0.256	-447	**-519****	(-990,-48.6), 0.031
Inpatient Costs	*76967*	518	763	443	635	493	491	-53	**-142**	(-530,245), 0.471	-247	**-279**	(-724,166), 0.219
ED Costs	*76967*	299	519	354	459	392	301	-115	**-150**	(-352,53), 0.147	-311	**-323****	(-572,-76), 0.011
Total Costs	*76967*	1772	2237	1953	2255	1770	1937	-163	**-246**	(-699,207), 0.287	-298	**-357**	(-897, 183), 0.195

**= Significant at 95% level, *=Significant at 90% level

Table 1.5: Biomarker and HEDIS Coefficients of Interest

		LT		MT		HT		LT:MT			LT:HT		
	N	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DiD	95% CI, p-value	Unadjusted DiD	Adjusted DiD	95% CI, p-value
Systolic BP	*22750*	129.3	130.5	129	131.3	127.7	128.6	1.10	**0.63**	(-0.89,2.16), 0.414	-0.30	**0.53**	(-1.89,2.95), 0.668
Diastolic BP	*22749*	78.5	78.4	79.2	79.7	81	80.3	0.60	**0.96****	(0.11, 1.82), 0.027	-0.60	**0.4**	(-1.01,1.81), 0.579
HbA1c	*11895*	7.97	7.86	7.95	8.02	8.01	7.96	0.18	**0.01**	(-0.25,0.28), 0.914	0.06	**-0.05**	(-0.55,0.44), 0.835
HEDIS													
Retina Exam	*82599*	0.49	0.41	0.64	0.59	0.75	0.62	0.03	**0.04**	(-0.01, 0.09), 0.119	-0.05	**-0.04**	(-0.12,0.04), 0.365
BP Control	*82599*	0.73	0.67	0.71	0.61	0.72	0.6	-0.04	**-0.04***	(-0.079,0.006), 0.094	-0.06	**-0.07***	(-0.0145,0.012), 0.098
Poor HbA1c Control	*82599*	0.34	0.42	0.33	0.38	0.37	0.43	-0.03	**-0.03**	(-0.038,0.04), 0.95	-0.02	**0.0006**	(-0.088,0.089), 0.99

**= Significant at 95% level, *=Significant at 90% level

Appendix: Tables and Figures

Table 1.A1: Telemedicine Claims-Based Definition

A Telemedicine visit is defined by any of the following codes:

Place of service code	**Note**
02	Must be included on professional claims
CPT Codes	
99441	
99442	
99443	
99201-99205	With modifier GT, 95, or V3
99211	With modifier GT, 95, or V3
99212	With modifier GT, 95, or V3
99213	With modifier GT, 95, or V3
99214	With modifier GT, 95, or V3
99215	With modifier GT, 95, or V3

Figure 1.A1: FQHC-level Telemedicine Visit Proportion

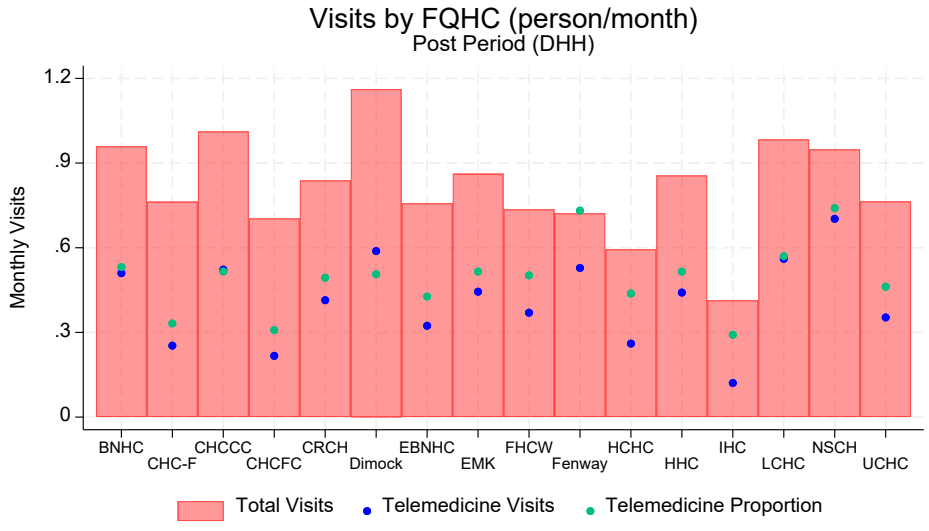


Table 1.A2: (cohort demographics)

Demographic	**Observations (n=94,581)**	**Beneficiaries (n=2,433)**
FQHC-level Telemedicine Exposure		
Low	10,084 (10.7)	304 (12.5)
Medium	80,172 (84.8)	2,019 (83)
High	4,325 (4.6)	110 (4.5)
Mean Age (SD)	53.7 (7.9)	52.3 (8.1)
Sex, N (%)		
Female	49,263 (52.1)	1,256 (51.6)
Male	45,318 (47.9)	1,177 (48.4)
Race, N (%)		
White, NH	28,351 (30)	733 (30.1)
Black, NH	15,063 (15.9)	391 (16.1)
Hispanic, any race	45,748 (48.4)	1,163 (47.8)
Asian or PI, NH	2,578 (2.7)	68 (2.8)
Other race	955 (1)	23 (1)
>1 race	806 (0.9)	22 (0.9)
Unknown	1,080 (1.1)	33 (1.4)
Primary Language, N (%)		
English	39,039 (41.3)	985 (40.9)
Spanish	30,914 (32.7)	766 (31.5)
Other Language	46 (0.1)	1 (0.04)
Unknown	24,582 (26)	681 (28)
Top 5 Zipcodes, N (%)		
01040	6,829 (7.2)	158 (6.5)

01902	6,378 (6.7)	160 (6.6)
02301	4,869 (5.2)	125 (5.1)
01610	3,700 (3.9)	92 (3.8)
01420	3,440 (3.6)	107 (4.4)
Condition, N (%)		
Mental Health History	71,869 (76)	1,824 (75)
Substance Use History	42,590 (45)	1,080 (44.4)
Asthma	30,456 (32.2)	752 (30.9)
Chronic Obstructive Pulmonary Disease	23,482 (24.8)	581 (23.9)
Cardiovascular Disease	34,480 (36.5)	870 (35.8)
Ischemic Heart Disease	25,224 (26.7)	637 (26.2)
Myocardial Infarction	7,188 (7.6)	179 (7.4)
Atrial Fibrillation	6,043 (6.4)	156 (6.4)
Cerebral Vascular Incident	9,236 (9.8)	234 (9.6)
Heart Failure	12,150 (12.9)	304 (12.5)

Table 1.A3: FQHC Telemedicine Group Categorization

LT	**MT**	**HT**
IHC	EBNHC	Fenway
CHC-F	HCHC	NSCH
CHCFC	UCHC	
	CRCH	
	FHCW	
	Dimock	
	HHC	
	EMK	

	CHCCC	
	BNHC	
	LCHC	

Figure 1.A2: FQHC Visit Modality over Time

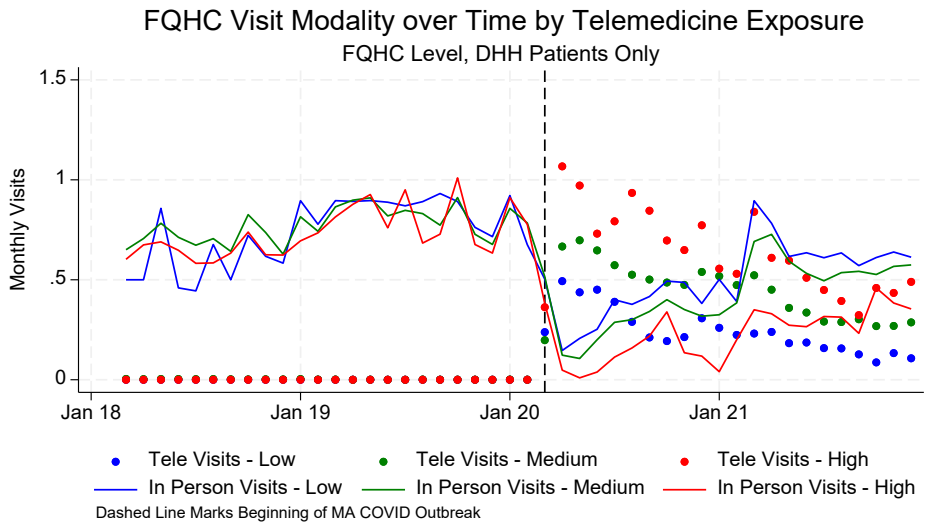


Table 1.A4: Parallel Trends Estimates

	Coefficient	**SE**	**Z**	**P-Value**
FQHC Total Visits / In Person Visits				
LT-MT	0.0022	0.0042	0.52	0.606
LT-HT	0.0098	0.0075	1.32	0.187
Outpatient Non FQHC				
LT-MT	0.0193	0.0124	1.56	0.118
LT-HT	0.0092	0.0166	0.55	0.58
Outpatient Total				
LT-MT	-0.0257	0.0144	-1.79	0.074

LT-HT	-0.0255	0.0257	-0.99	0.321
Inpatient Visits				
LT-MT	-0.0004	0.0006	-0.67	0.503
LT-HT	0.0002	0.0008	0.25	0.805
ED Visits				
LT-MT	-0.0008	0.0021	-0.38	0.703
LT-HT	-0.0020	0.0029	-0.7	0.485
Outpatient Costs				
LT-MT	-14.95	17.79	-0.84	0.401
LT-HT	-32.00	24.83	-1.29	0.197
Outpatient - Professional Costs				
LT-MT	-17.16	18.30	-0.94	0.348
LT-HT	-33.51	25.49	-1.31	0.189
Inpatient Costs				
LT-MT	-12.97	17.43	-0.74	0.457
LT-HT	-22.96	24.34	-0.94	0.345
Emergency Department Costs				
LT-MT	4.03	10.35	0.39	0.697
LT-HT	-16.73	14.46	-1.16	0.247
Total Costs				
LT-MT	-18.05	19.44	-0.93	0.353
LT-HT	-31.07	27.05	-1.15	0.251
Min Systolic BP				
LT-MT	0.13	0.08	1.49	0.136
LT-HT	-0.01	0.12	-0.05	0.963
Min Diastolic BP				

LT-MT	0.01	0.05	0.22	0.825
LT-HT	-0.09	0.07	-1.2	0.232
Min HbA1c				
LT-MT	0.021	0.013	1.64	0.1
LT-HT	0.020	0.018	1.15	0.248
HEDIS: Retina				
LT-MT	**0.0054192***	0.001	4.31	0
LT-HT	-9.58E-04	0.002	-0.58	0.564
HEDIS: BP				
LT-MT	-2.12E-03	0.002	-1.41	0.16
LT-HT	-2.03E-03	0.002	-1.02	0.307
HEDIS: HbA1c				
LT-MT	-2.18E-03	0.002	-1.4	0.162
LT-HT	-4.35E-03	0.003	-1.57	0.116

CHAPTER 2: Quantifying the Effects of Increased Patient Portal Use on Health, Health Care Utilization, and Disparities amongst Rhode Island Residents

Introduction

Patient portals are web-based platforms that enable patients to access their medical records (including medical history, laboratory results, and prescribed medications) (55). Portals can allow patients to schedule appointments, request prescription fills, and asynchronously chat with providers. Despite these capabilities, early investment in portals had been minimal until the passage of the HITECH Act in 2009. This piece of legislation directed 36.5 billion dollars towards modernizing United States' Health Information Technology (IT) (56). This included helping organizations make personal electronic health data available to patients so they can receive "meaningful use" incentives payments (57). Such legislation spurred increased patient portal development and implementation. Around the same time, the Blue Button project was launched, which aimed to develop a simple way for patients to download personal health information (58). This project gained support from insurers, providers, and health IT companies (59).

The passage of HITECH led to increases in both patient portal access and use (60). Empirical analyses showed that portal non-users "were more likely to be male, be on Medicaid, lack a regular provider, and have less than a college education, compared to users" (61). These patients, and non-White populations, were also less likely to report being offered access (61). Regarding patient outcomes, improved access and usage has been associated with increased shared decision-making, reduced medical errors, and improved selected health outcomes (62-71). Increased portal use, however, may also exacerbate health inequities, reinforcing the "digital divide" (12, 15, 55, 72). The "digital divide", as described in chapter 1, is a phenomenon where technology use is concentrated amongst healthier populations at baseline, contributing to widening disparities. If this effect is mitigated, chronically ill persons from underserved backgrounds stand to experience large benefits from portals (73).

Portal use witnessed considerable increases during the COVID-19 pandemic, which has persisted into the present (74). This trend may demonstrate the increasingly important role patient portals play in increasingly hybrid health care settings. In addition to portals being useful places to receive and understand COVID-19 test results, they also can facilitate virtual communication with providers, schedule appointments, and place prescription orders. As COVID-19 becomes less dire, the scope of patient portals will need continued evaluation.

Specific focus on the influence of patient portals must be paid to patients with one or multiple chronic conditions (multimorbidity). As of 2018, 51.8% of non-institutionalized adults had been diagnosed with at least one chronic condition; 27% of adults were diagnosed with multiple conditions (23). Further, amongst subgroups, those with public insurance and those living in rural areas constituted higher than average multimorbidity prevalence (23). This group is also comprised of high-need and high-cost patients, as prior research states that the cost and health effects of multimorbidity is multiplicative rather than additive (24, 25). This population could potentially benefit from active portal use due to their conditions requiring frequent interaction with providers, medication adherence, and patient-level health literacy. Indeed, prior research has shown an increase in portal use amongst rural-dwelling patients with more chronic conditions (75).

Relatively common conditions like Diabetes Mellitus, Hypertension, and Hyperlipidemia (DHH) can be better managed by adhering to these strategies. The current body of relevant research suggests that portals potentially helps these chronic populations, (73, 76-88) so focusing on a potential incremental relationship between portal use and health outcomes for this population is an important extension to the knowledge base. Ultimately, understanding how increased portal use influences outcomes, particularly after an exogenous health shock, is crucial to evaluating the successes and opportunities of current patient portal systems. Thus, our objective with this research was to assess how use of patient portals affected quality of care and health care costs for all patients, as well as for patients with Type II Diabetes.

Methods

Data

To answer these questions, this research uses data from CurrentCare, Rhode Island's Health Information Exchange (HIE), managed by the Rhode Island Quality Institute. Current Care includes approximately half of the state's nearly 1.1 million residents, including about 45 million patient visits. In addition to inpatient and outpatient visits, CurrentCare also includes 90% of lab tests and prescription fills. Its data originate from primary care and specialty practices, community health centers, hospitals, long-term care facilities, and visiting nurse agencies. In addition to these data, CurrentCare also manages a patient portal, labeled CurrentCare for Me. While this portal doesn't allow for real-time interaction with providers, patients can view recent test results, download their medical record, and send/receive messages from providers. The analytic data set for this research merges HIE data from a variety of sources, including visits, medications, and diagnosis files. Further, this research incorporates data on the total number of portal visits to each of the sub-sites within the portal. The list of sub-sites we track are listed in Table 2.A1 in the appendix. This research is the first documented use of Current Care for Me data.

Sample

To be included in the study, patients must have been adult (greater than 18 years old) CurrentCare enrollees with at least one outpatient visit between 2016 and 2019 and one outpatient visit between 2020 and 2022 to ensure our sample has a baseline level of care engagement. Further, these patients must have a documented Rhode Island home zip code, and have visited a provider practicing at a Rhode Island health care facility. In order to fully capture a patient's chronic disease burden, only those with non-missing diagnosis or problem data were included.

Treatment Definition

Our treatment group can be defined as people who have documented portal views. These patients are segmented into two groups, moderate portal users and high portal users. Moderate portal users are defined as having between 1-14 documented portal page views. High portal users are defined as having at least 15 portal page views. The cutoff for these groups was done to ensure both treatment levels are sufficiently powered for these analyses. These two treatment groups are compared against the control group, which includes patients with 0 documented portal page views. Due to the large size of the control group, we randomly drew a control population approximately four times larger than all portal users.

It is important to note that portal use isn't time-stamped in these data, thus hampering the ability to definitively infer causality from person-level portal use. We assume that the majority of portal use occurred post-COVID onset, which aligns with available data on portal usage trends over time. We discuss the ramifications of this limitation in the discussion.

Outcomes

Study outcomes can be grouped into two distinct categories. The utilization outcomes include total visits, visits to outpatient facilities, inpatient facilities, emergency departments (ED), and labs. These outcomes help approximate CurrentCare patients' level of care engagement in addition to the incidence of downstream health events. The second set of outcomes pertain to clinical biomarker results, outcomes include measures related to recorded lab and vital data on A1c, blood pressure (BP), and LDL. These measures, particularly for patients with chronic conditions, help to approximate CurrentCare patients' chronic disease management and day-to-day health status. After excluding extremely outlying measurements, these outcomes are measured at the month level. Where multiple measurements are recorded in a given month, the mean value is used.

Statistical Analysis

To estimate the effects of significant patient portal use, we use a difference-in-differences approach with linear models to examine differences in patient-level outcomes between portal users and non-portal users before (January 2016-March 2020) vs. after (April 2020-December 2022) the onset of COVID-19 in the United States. The general functional form of these models is depicted below in equation (1), estimating outcome *Y* for person *i* in month *m*:

$$(1) \qquad Y_{im} = \beta_0 + \beta_1 Post_m + \beta_2 Portal_i + \beta_3 Time_m Portal_i + \beta_4 X_i + \propto_m + \varepsilon_i$$

$Post_m$ is a binary indicator that represents an observation occurring in period either before or after COVID-19 onset. $Portal_i$ represents whether the observation is a portal nonuser, a some-use portal user, or a high-use portal user. The covariate of interest (β_3) estimates the effect of being a portal user after COVID-19 onset on a given outcome. Additionally, models are adjusted for a vector of patient level covariates (X_i), and include month-year ($\propto_m$) fixed effects.

The covariates for this analysis include patient age, sex, race, prevalence of 20 relevant chronic comorbidities, 3-digit zip code, and housed status. Additionally, these models use robust variance estimators. These analyses are conducted both with the full sample and with sub-samples of those diagnosed with Type II Diabetes. Further, clinical biomarker analyses are conducted on their respective chronic condition population. This includes Blood pressure for hypertensive people, HbA1c for Type II Diabetics, and LDL for people with Hyperlipidemia. Statistical significance is determined at the 95% level. Further, to account for the selection issues present with person-level treatment assignment, we also leverage inverse probability weighting based on observable baseline characteristics.

Such a model relies on the parallel-trends assumption, which states that time trends in outcomes followed the same trajectory prior to the pre/post cut-off. To address this, we present figures for each outcome to support this assumption. Further, we statistically test these trends to ensure they follow a parallel path. For the full sample, the parallel trends assumption is largely satisfied. There are three models, however, that see potential violations with the full sample. As we see in chapter 1, there are a couple outcomes that see potentially divergent trends early in the pre-period, which become parallel before the intervention. This occurs within the outpatient visits, ED visits, and Lab visits models. To test this, we truncate the sample, while still keeping at least two years of pre-period data. For outpatient and lab visits, we exclude the first 14 months, for ED visits we exclude the first 36. As in chapter 1, when we run the primary models with these truncated samples, the effect estimates remain significant with a similar model to the models using the full sample. Thus, we posit that the potential violation in parallel trends does not materially alter the interpretation of results.

Similar to chapter 1, these models rely on consistency, exogeneity, and positivity (43). There is no reason to suggest that observed treatment differs from counterfactual treatment, suggesting the consistency assumption is satisfied. Baseline levels of outcomes did not determine treatment assignment, suggesting the exogeniety assumption is satisfied. The positivity assumption requires that each patient in this population could exist in each treatment group. While efforts to increase broadband access nationwide continue, it is estimated that 91% state households use an internet-connected device, and 100% have one available to them (89). While the satisfaction of these assumptions could be strengthened with additional data, these findings can indicate the presence of relationships worth examining further.

Sensitivity Analysis

To further examine the relationship between portal and these various health outcomes, we conduct additional analyses based on specific types of portal usage. As described above, the CurrentCare data allow for analysis of sub-site visits within the portal. We hypothesize that some of these sites better signify a patient's intent to use the portal as a proactive care engagement tool. For example, patients using the "library" and "wellness" pages may be more inclined to use the portal to better understand how to manage their conditions than patients who use the portal to review their allergy information (of which they are conceivably already aware). Identifying treatment based upon these specific visits helps better understand what types of portal visits drive our results. To identify treated observations in these analyses, we identified the page view distribution of each sub-site, and enforced a cutoff where treated observations comprised approximately 10% of all observations.

Results

The demographics of our patient population by treatment status can be seen in Table 2.1. Our sample is comprised of 2,554,469 million observations (patient-months), originating from 107,212 people. In terms of treatment categories, our control group, 'no use' (NU) comprised 84% of all observations, and the 'some use' (SU) and 'high use' (HU) groups comprised 9% and 7%, respectively. Portal visits had a heavily right-skewed distribution, with people seeing a mean number of 5.4 portal visits. From this, we observe that portal users are slightly more likely to be younger, more likely to identify as White and as female, and more likely to reside in a '028' zip code. Further, portal users have a lower prevalence of most chronic conditions and are less likely to be unhoused. When we compare (via chi-squared tests) our categorical variables by treatment status, we find that each variable is significantly associated with portal use level at the 95% level. To see demographics irrespective of treatment status, please see Table 2.A3.

As previously mentioned, a key assumption with a difference-in-difference methodology relies on outcomes pre-period trends being parallel. Such an assumption signifies that, in the absence of exogenous shocks, outcome differences between treatment and control groups would remain constant. This is shown in Figures 2.1a-2.1i, which shows the unadjusted trends for each of the primary outcomes. These figures show treatment groups following similar trajectories prior to

pandemic onset. Further, the results of our statistical analysis to confirm parallel trends is visible in Table 2.A2. Similar to chapter 1, most outcomes satisfy this assumption, but some potentially violate it. For outpatient, inpatient, and lab visits, we observe that while estimates closer to March of 2020 are parallel, the earliest months may be trending differently. Running the difference-in-differences estimates with the full dataset and with the early months excluded yield near-identical estimates. Thus, given these additional checks, we can credibly argue that these assumptions are also valid, except for Lab Visits (NU-HU) and Diastolic BP (NU-SU).

Table 2.2 displays the results of the primary analyses, using inverse probability weights. When focusing on outpatient visits, the coefficient of interest indicates that SU portal users see 0.07 fewer total monthly visits (CI: [-0.11,-0.03], p-value=0.001) after pandemic onset than the control group. In terms of ED visits, HU treated observations observed 0.02 fewer monthly ED visits (CI: [-0.03,-0.01], p-value < 0.001) Lab visits saw portal users having more monthly lab visits with SU and HU groups seeing 0.09 and 0.13 more monthly visits than control observations, respectively (SU: CI: [0.07,0.12], p-value<0.001, HU: CI: [0.1,0.16], p-value<0.001).

When running these models within our Diabetic cohort, the ED model sees the only significant results. SU observations saw 0.04 fewer total visits than control observations (CI: [-0.07,-0.002], p-value=0.038). HU observations saw 0.06 fewer total visits than control observations (CI: [-0.09,-0.003], p-value<0.001). These estimates are displayed in Table 2.3.

When focusing on biomarker estimates, we observed mostly null effects, with significant effects being observed in the A1c and Diastolic BP models. SU observations saw 0.1% increased HbA1c than NU observations (CI: [0.01,0.019], p-value=0.03). SU observations saw a 0.55-unit lower Diastolic BP than control observations (CI: [-1.02,-0.08], p-value=0.021). These estimates can be seen in Table 2.4.

Sensitivity Analysis

Table 2.5 shows the coefficients of interest for each portal sub-site, by treatment group. For each model, the outcome is outpatient visits. The two sub-sites with significant effect estimates are ‘Contacts’ and ‘Inbox’.

Discussion

Taken together, these results suggest that portal users saw more health care utilization than non-portal users, especially after COVID-19 onset. These results hold for more upstream outcomes like outpatient and lab visits, while downstream

outcomes appear to be relatively equal across treatment groups. Such a result extends the current knowledge base, which had yet to quantify this in the presence of an exogenous shock. This could be the result of a confluence of factors, including patient demographics, improved care coordination, or associations with other healthy behaviors (90). We find that those who use patient portals tended to be White, female, healthier, and younger, which is consistent with the existing patient portal knowledge base (61). These demographics are both more likely to contribute to increased portal use and improved outcomes, which is why they are adjusted for in all regression models.

In our primary models with our full sample, we observed portal users and non-portal users to have similar pre-pandemic care utilization. Even though patient portal users may differ from non-users at baseline, covariate adjustment accounts for some of these differences. Further, patient portal use has increased over time (including a shift upwards after pandemic onset), so it is fair to suggest that portal use would see a lower potential effect prior to March of 2020. As it pertains to downstream utilization, however, we saw portal users largely see COVID-19 onset have an equal effect on inpatient, and emergency monthly visits. This aligns with previous research, and extends its implications logically. Previous research has shown that portal users, particularly those with chronic conditions, experience reductions in ED visits and preventable hospitalizations (81, 91-93). Such findings are likely due to portals' assistance in managing providers, medications, and lab schedules, contributing to better health maintenance (81, 93). Unfortunately, previous portal research is limited due to low portal utilization from the general patient population.

The introduction of a global pandemic, however, led to a larger demonstrated need for all patients to receive care and health information virtually. Increased outpatient and decreased ED monthly visits for portal users post-pandemic onset suggests that previously documented portal benefits prove themselves to be even more helpful when in-person care is less tenable. Importantly, outpatient visits in this sample include telehealth visits, which are facilitated by active patient portal use. Thus, portals appear to function as useful care management tools that facilitate care management, especially for those who find it tough to receive in-person care.

Our analysis of outpatient visits, however, yields different conclusions. Portal users appear to have higher monthly outpatient visits than non-portal users. This has been seen in previous research, as portal users tend to use it in relation to previous and upcoming outpatient visits. Further, portal users are also more likely to be actively engaged in routine care (81). This difference, however, is negated in the post period, with portal users seeing slightly fewer outpatient visits than non-portal users. We believe this could occur through the mechanism of portal users substituting portal views for certain

in-person visits (81, 94), which non-portal users cannot conceivably do. Models estimating lab visits also have interesting implications. Portal users had fewer lab visits in the pre period, which aligns with the models on downstream health events (implying that portal users are healthier at baseline). These differences are essentially neutralized post pandemic onset, potentially due to the increase in COVID testing visits, largely seen among highly engaged patients. Further, treated observations likely used the portal to view test results, suggesting these patients' care was made more seamless through accessing this portal.

The models focusing on patients with chronic conditions prompt further discussion. Outside of decreased ED visits, these estimates do not appear statistically significant. Thus, amongst this sicker cohort, while portal use may not be shown to be clearly associated to increased outpatient care, there may be a tangible effect on preventable ED admissions. This aligns with previous research identifying that portals can especially help chronic condition patients by coordinating their more involved care management and medication schedule (73, 81).

While effects on ED utilization are significant amongst Type II diabetics, COVID-19 onset did not appear to be associated with significant differences in clinical biomarkers between control and treated observations. This lack of an effect could be due to a couple explanations. Fewer observations were involved in these models, lowering their power. Second, differences in these outcomes may take longer to show in these models, and further analyses with more months of data may be valuable. Despite these results, portal users did possess lower HbA1c and Systolic BP levels than non-portal users at baseline. Such a finding, while perhaps not caused by increased portal use, is indicative of more proactive disease management facilitated by patient portal functionalities.

Sensitivity analyses demonstrated that certain portal sub-sites did have a larger association with outcome changes than others. While the "Contacts" sub-site is visited most frequently, the "Inbox" sub-site had the strongest relationship with improved outcomes. Given that this is the source of the most direct correspondence with providers, this relationship makes sense. Even though there isn't functionality for live patient/provider dialogue, our results support the usefulness of read-only portals while also underscoring the importance of enhancing that functionality in future portal iterations.

The collection of this research possess important implications for HIEs and patient portals. HIEs like CurrentCare provide a valuable resource, despite limited initial adoption after HITECH's passage (95, 96). CurrentCare's ability to synthesize data from multiple sources to more fully tell patients' medical stories is necessary as distinct systems continue to strive for

improved interoperability. Further, continued support must be given to HIEs to support infrastructure development, as well as to providers and patients on how to best make use of HIEs and patient portals. This includes ensuring that disclosing sensitive and complex information continues via in-person communication (97). Recent state legislation aims to adjust CurrentCare from an "opt-in" framework to an "opt-out" framework (98). Such policy is important, but must be supplemented with patient-level engagement to best leverage HIE capabilities. The current health care landscape sees a proliferation of provider portals. For patients with a variety of providers, this fragmentation is likely to cause annoyance at best, and disrupted care at worst. HIE portals offer a solution to collectively house all data under one log-in, and this research suggests that this is of significant value.

Patient portals are valuable tools, but research like this emphasizes the additional effort required to maximize their utility. Portals provide valuable access to personal health information, and can improve health care engagement and health status, especially amongst vulnerable populations. (73, 78, 87, 88) This research supports these claims, especially as it pertains to health care utilization. Further, we find that exogenous shocks that require more virtual health care widens these differences. This is especially noteworthy within a population with a relatively high health literacy baseline (patients who have opted into CurrentCare). Our findings support the importance of encouraging portal use, especially amongst subpopulations who historically have accessed portals at lower rates (non-English speakers, non-White and older patients, and those with lower health and technological literacy) (15, 78, 86, 99). Such efforts will likely require policy focusing on identifying who needs assistance, who will provide it, and how it will be reimbursed (48, 100). With the recent end of the COVID-19 public health emergency, extra care needs to be taken to make sure those that benefitted from virtual care during this period maintain affordable access. Future research will evaluate how these effects differentially impact different sub-groups (especially racial and ethnic populations), which will be approached in chapter 3.

Despite this, there are limitations to this work. First, the structure of the patient portal file limits causal claims. While we have data on portal use, these data aren't currently tied to dates. Thus, we have no ability to tie portal use directly to outcomes in future weeks or months. Future research will incorporate time-stamped portal data, but currently we operate off the assumption that portal use is relatively evenly distributed throughout the time period. Second, we also would like to have data on unique portal sessions in addition to portal visits. This would allow for further comparisons between those who use the portal numerous times with limited engagement at each visit, and those who use it sparingly, but visit many sub-sites during each session. These data will also be available in the future for continued research. Third, we would like

to incorporate cost and insurance status into future analyses, as prior research has shown that increased portal use is associated with being uninsured or being on Medicaid (61, 86). This would also allow for more nuanced discussion concerning cost effectiveness of portal development and activation, which would help inform ongoing policy debates. Finally, while this is a comprehensive data set, it only captures information from one HIE from a small state which could potentially limit external validity.

Ultimately, however, we believe this research offers important insights on the how portal use is related to various health and health care outcomes, especially after an exogenous shock necessitates remote care. This is the first foray into CurrentCare for Me analysis, and hopefully this research lays a foundation for future analyses on this valuable health care resource.

Conclusion

Amongst patients enrolled in a HIE, patient portal users were more likely to engage in more care management, and experience fewer adverse events than non-portal users. For total, emergency, and inpatient visits, these gaps largely remain unchanged after COVID-19 onset, while portal users see increased outpatient visits. Within our Diabetic cohort, we see reduced ED visits for portal users. Certain portal sub-sites drove these results, including “Inbox” and “Contacts”, suggesting these views led to direct provider interaction. Portals function as a useful tool for ongoing care management, which is especially important when virtual care is a preferred modality.

Tables and Figures

Table 2.1: Demographics by Treatment Group

By Levels of Portal Use	**No Use**	**Some Use**	**High Use**
Observation Level	*n=2,168,016*	*N = 239,186*	*N = 167,410*
Mean Portal Visits (SD)	0 (0)	6.1 (3.8)	88.9 (194)
Mean Age (SD)	58.4 (16.7)	53.3 (15.9)	52.5 (15.7)
Female (%)	1383560 (64.4)	170552 (71.3)	122349 (73.1)
Race (%)			
White	1452472 (67.6)	190164 (79.5)	137086 (81.9)
Black	131673 (6.1)	7006 (2.9)	3594 (2.2)
Hispanic	108052 (5)	7212 (3)	3688 (2.2)
Asian	25290 (1.2)	3306 (1.4)	1980 (1.2)
Other	430386 (20)	31498 (13.2)	21062 (12.6)
3-Digit Zip: 029 (%)	755388 (35.2)	69575 (29.1)	50668 (30.3)
Unhoused	31213 (1.5)	1004 (0.42)	664 (0.40)
Diabetes	473094 (22)	36527 (15.3)	22404 (13.4)
Hypertension	1208545 (56.3)	104520 (43.7)	70149 (41.9)
Hyperlipidemia	1018546 (47.4)	91471 (38.2)	62734 (37.5)
DHH	338785 (15.8)	23135 (9.7)	15148 (9.1)
Angina	236260 (11)	16503 (6.9)	12285 (7.3)
Heart Failure	212952 (9.9)	12092 (5.1)	8578 (5.1)

Peripheral Artery Disease	18597 (0.87)	1276 (0.5)	709 (0.4)
AIDS	8891 (0.4)	768 (0.3)	439 (0.3)
Connective Tissue Disease	4464 (0.2)	662 (0.3)	323 (0.2)
Rheumatoid Arthritis	52081 (2.4)	4383 (1.8)	3799 (2.3)
Dementia/Alzheimers	66189 (3.1)	3618 (1.5)	2334 (1.4)
Multiple Sclerosis	17773 (0.8)	2453 (1)	2097 (1.3)
Parkinson's	2891 (0.1)	155 (0.1)	105 (0.1)
Stroke	66388 (3.1)	4439 (1.9)	3232 (1.9)
Cancer	181816 (8.5)	16053 (6.7)	12319 (7.4)
Glaucoma	54660 (2.5)	4174 (1.8)	2437 (1.5)
Depression	376115 (17.5)	37873 (15.8)	25775 (15.4)
Alcohol Abuse	89880 (4.2)	4389 (1.8)	3479 (2.1)
Asthma	408204 (19)	42162 (17.6)	31507 (18.8)
COPD	104128 (4.9)	5009 (2.1)	4180 (2.5)
Chronic Kidney Disease	215916 (10.1)	15136 (6.3)	10370 (6.2)

Note: Each categorical variable is associated with FQHC category (95% level)

Figures 2.1a-2.1i: Unadjusted Outcome Trends

Figure 1a: Total Visits

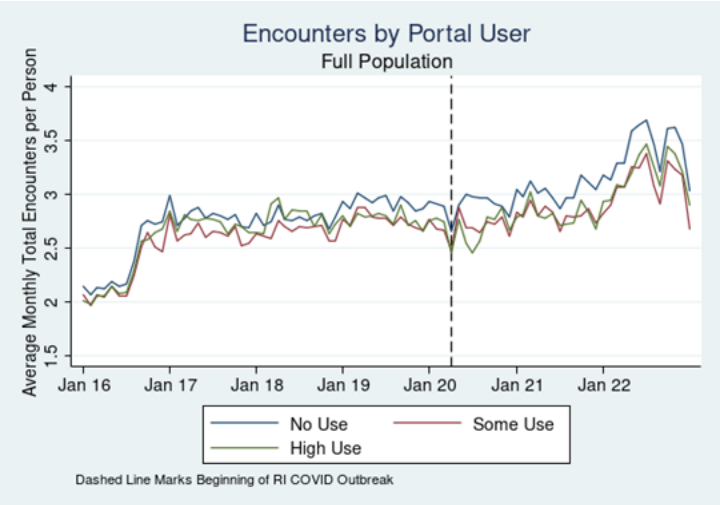


Figure 1b: Outpatient Visits

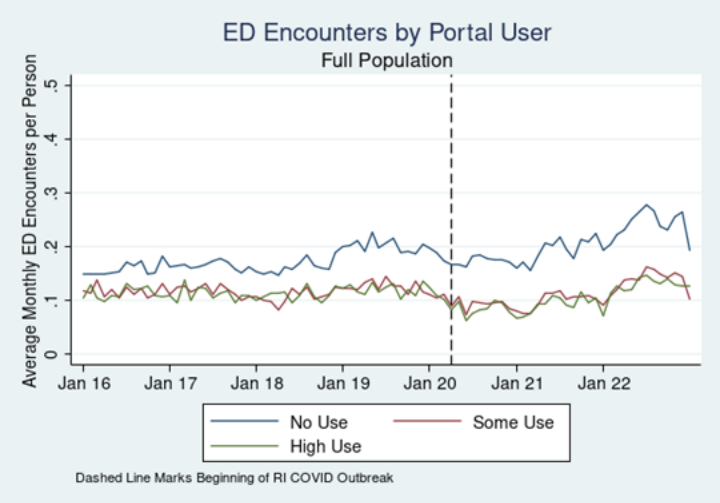


Figure 1c: Inpatient Visits

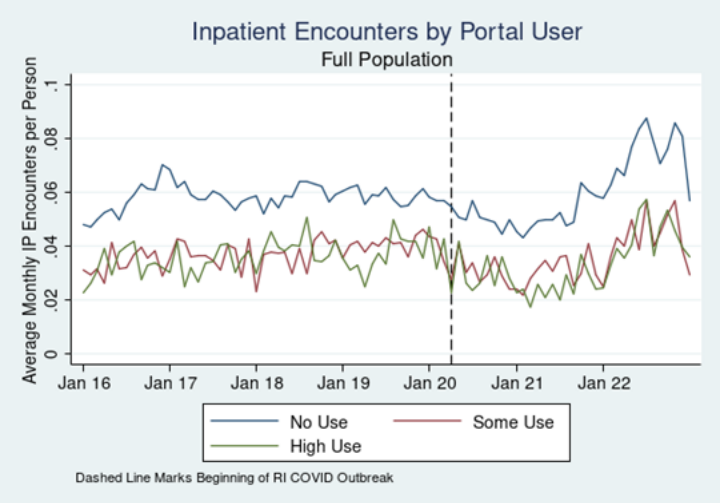


Figure 1d: Outpatient Visits

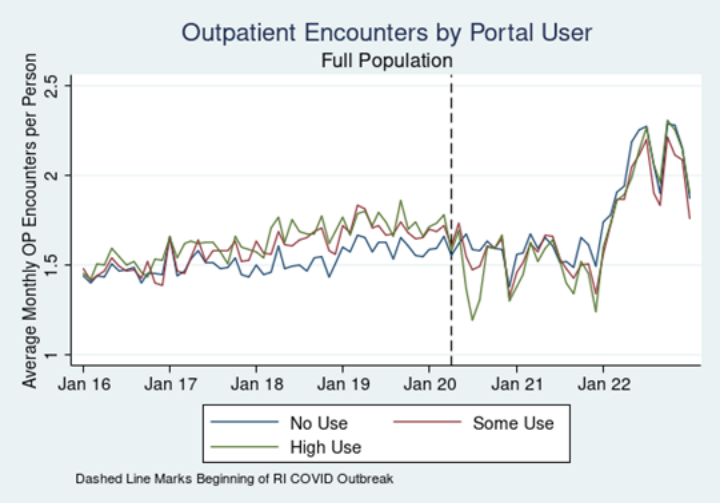


Figure 1e: Lab Visits

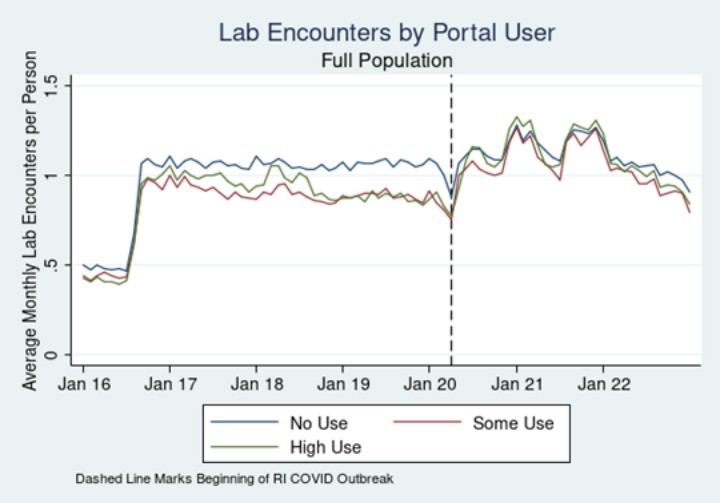


Figure 1f: Blood Glucose Pre Trends (Diabetics)

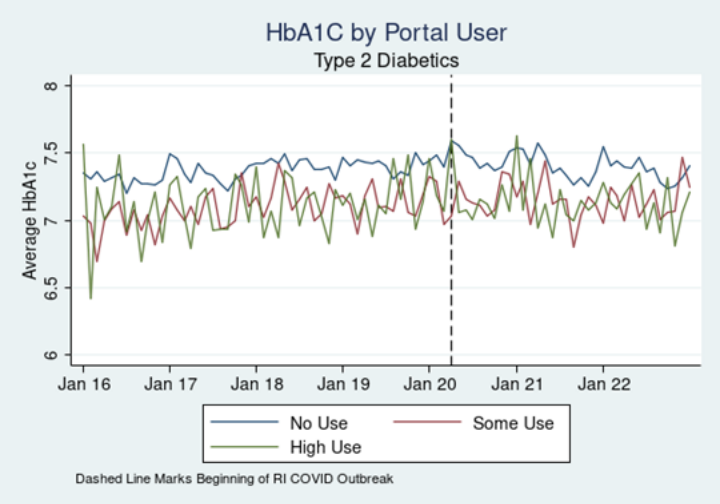


Figure 1g: Systolic BP (Hypertensive Population)

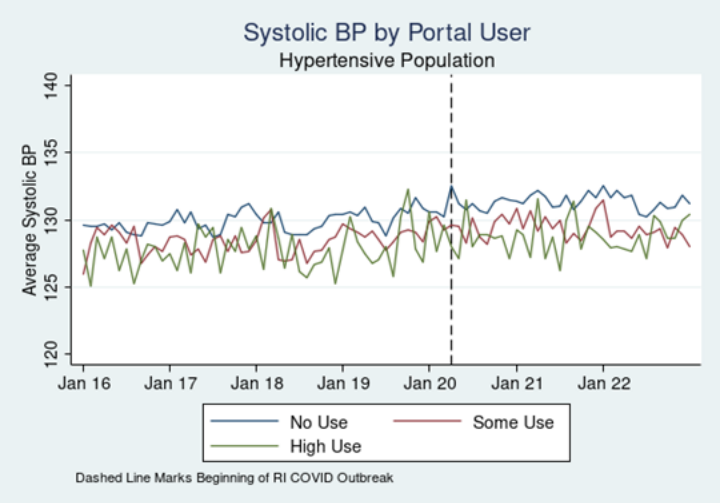


Figure 1h: Diastolic BP (Hypertensive Population)

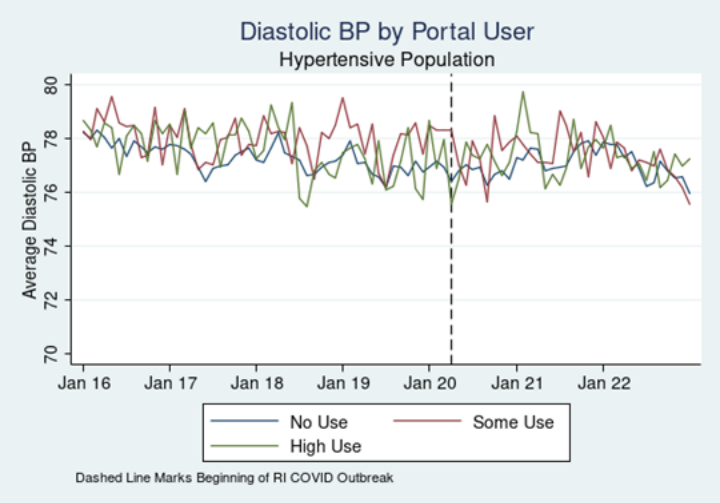


Figure 1i: LDL (People with Hyperlipidemia)

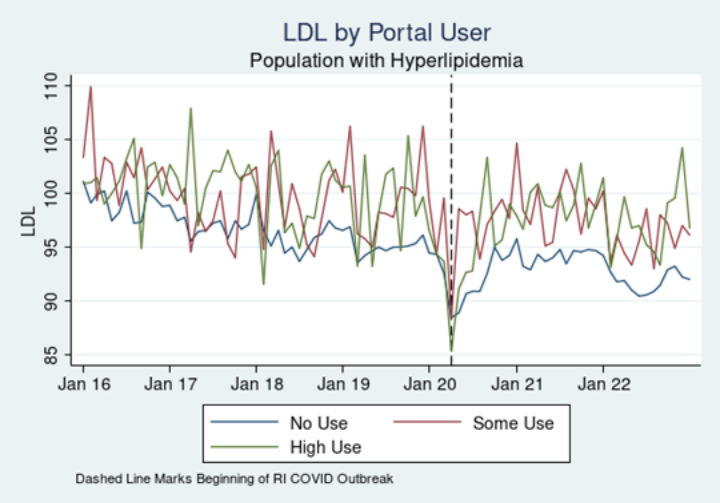


Table 2.2: Main Regression Output Coefficients of Interest (Full Cohort)

		NU		SU		HU		NU:SU			NU:HU		
	N	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DiD	95% CI, p-value	Unadjusted DiD	Adjusted DiD	95% CI, p-value
Total Visits	*2532627*	2.74	3.15	2.62	2.89	2.68	2.9	-0.14	**0.005**	(-0.06,0.07), 0.867	-0.19	**0.04**	(-0.04,0.12), 0.323
Outpatient Visits	*2532627*	1.52	1.76	1.62	1.68	1.66	1.65	-0.18	**-0.07****	(-0.11, -0.03), 0.001	-0.25	**-0.06**	(-0.13,0.0008), 0.053
ED Visits	*2532627*	0.17	0.21	0.12	0.11	0.11	0.1	-0.05	**-0.02**[f]	(-0.03, -0.002), 0.023	-0.05	**-0.02****	(-0.03,-0.01), <0.001
Inpatient Visits	*2532627*	0.058	0.06	0.038	0.035	0.036	0.032	-0.005	**-0.002**	(-0.007,0.003), 0.466	-0.006	**-0.004**	(-0.01,0.003), 0.296
Lab Visits	*2532627*	0.98	1.12	0.85	1.07	0.87	1.12	0.08	**0.09****	(0.07,0.12), <0.001	0.11	**0.13****	(0.10,0.16), <0.001

*= Significant at 95% level

Table 2.3: Main Regression Output Coefficients of Interest, Diabetic Cohort

		NU		SU		HU		NU:SU			NU:HU		
	N	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DiD	95% CI, p-value	Unadjusted DiD	Adjusted DiD	95% CI, p-value
Total Visits	*527168*	3.14	3.77	3.02	3.5	3.27	3.71	-0.15	**-0.07**	(-0.24,0.11), 0.467	-0.19	**-0.07**	(-0.29,0.16) 0.569
Outpatient Visits	*527168*	1.78	2.15	1.85	2.09	2.01	2.29	-0.13	**-0.07**	(-0.19, 0.05), 0.281	-0.09	**-0.03**	(-0.21, 0.14), 0.702
ED Visits	*527168*	0.16	0.26	0.11	0.15	0.1	0.13	-0.06	**-0.04***	(-0.07, -0.002), 0.038	-0.07	**-0.06***	(-0.09,-0.03), <0.001
Inpatient Visits	*527168*	0.081	0.099	0.054	0.07	0.057	0.065	-0.002	**-0.004**	(-0.02,0.01), 0.547	-0.010	**-0.01**	-0.03, 0.01) 0.323
Lab Visits	*527168*	1.12	1.27	1.01	1.2	1.09	1.23	0.04	**0.06**	(-0.007,0.12), 0.084	-0.01	**0.04**	(-0.03,0.11), 0.247

*= Significant at 95% level

Table 2.4: Biomarker Regression Output Coefficients of Interest (Chronic Condition Cohorts)

		NU		SU		HU		NU:SU			NU:HU		
	N	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DiD	95% CI, p-value	Unadjusted DiD	Adjusted DiD	95% CI, p-value
A1c	*113215*	7.38	7.4	7.11	7.15	7.11	7.13	**0.02**	**0.10***	(0.01,0.19), 0.03	**0**	**-0.02**	(-0.14,0.1), 0.696
Systolic BP	*184485*	130	131.3	128.5	129.2	127.9	128.9	**-0.60**	**-0.42**	(-1.16,0.33), 0.276	**-0.30**	**-0.26**	(-1.25,0.72), 0.605
Diastolic BP	*184485*	77.3	77	78	77.2	77.6	77.3	**-0.50**	**-0.55***	(-1.02,-0.08), 0.021	**0**	**0.029**	(-0.55,0.61), 0.922
LDL	*226209*	96.5	92.9	99.6	97.5	99.8	97.7	**1.50**	**0.53**	(-0.79,0.185) 0.433	**1.50**	**0.16**	(-1.51,1.83), 0.848

*= Significant at 95% level

Table 2.5: Sub-Site Coefficients of Interest (Sensitivity Analysis)

Full Cohort	**SU**	**HU**
Library	--	--
Allergy	--	--
Contacts	**-0.07***	--
Diagnoses	--	--
Visits	--	--
Illness History	--	--
Inbox	**-0.13***	--
Lab	--	--
Radiology Order	--	--
Wellness	--	--
Observations	--	--

*= Significant at 95% level

Appendix: Tables and Figures

Table 2.A1: Portal Sub-Sites

Portal Sub-Sites
Library
Allergy
Contacts
Diagnoses
Visits
Illness History
Inbox
Lab
Rad Order
Wellness
Observations

Table 2.A2: Parallel Trends Estimates

Total Visits	**Coefficient**	**SE**	**Z**	**P-Value**
NU-SU	-1.1 E -03	7.9 E -04	-1.36	0.174
NU-HU	-1.8 E -03	1.1 E -03	-1.59	0.111
Outpatient Visits (after 14 months)				
NU-SU	1.6 E -03	9.2 E -04	1.77	0.077
NU-HU	1.3 E -03	1.3 E -03	1.01	0.31
ED Visits (after 36 months)				
NU-SU	-1.5 E -04	6.3 E -04	-0.23	0.82
NU-HU	7.2 E -05	7.2 E -05	0.09	0.93

Inpatient Visits				
NU-SU	1.76 E -05	6.4 E -05	0.27	0.78
NU-HU	-1.8 E -05	6.7 E -05	-0.26	0.79
Lab Visits (after 14 months)				
NU-SU	-9.9 E -05	4.7 E -04	-0.21	0.83
NU-HU	-3.2 E -03	6.2 E -04	-5.1	0
Blood Glucose				
NU-SU	2.5 E -03	1.7 E -03	1.52	0.129
NU-HU	3.2 E -03	2.1 E -03	1.53	0.126
Systolic BP				
NU-SU	3.9 E -03	0.01	0.31	0.76
NU-HU	1.1 E -03	0.02	0.07	0.95
Diastolic BP				
NU-SU	**0.02***	8.5 E -03	2.33	0.02
NU-HU	3.8 E -03	0.01	0.36	0.72
LDL				
NU-SU	0.02	0.02	0.8	0.42
NU-HU	0.02	0.03	0.65	0.52

Table 2.A3: Cohort Demographics

	Patient-Months	**People**
Portal Use Levels (%)	*N=2,554,469*	*N= 107,212*
No use (0 Views)	2147873 (84.1)	89569 (83.5)
Some use (1-14 Views)	239186 (9.4)	10516 (9.8)
High Use (15+ Views)	167410 (6.6)	7127 (6.7)

Mean Portal Visits (SD)	6.39 (54.3)	5.40 (41)
Mean Age (SD)	57.5 (16.7)	54.2 (17.2)
Female (%)	1676461 (65.6)	63501 (59.2)
Race (%)		
White	1779722 (69.7)	73034 (68.1)
Black	142273 (5.6)	5951 (5.6)
Hispanic	118952 (4.7)	5255 (4.9)
Asian	30576 (1.2)	1740 (1.6)
Other	482946 (18.9)	21232 (19.8)
3-Digit Zip: 029 (%)	875631 (34.3)	36991 (34.5)
Unhoused	32881 (1.3)	1029 (1)
Diabetes	532025 (20.8)	15525 (14.5)
Hypertension	1383214 (54.2)	46025 (42.9)
Hyperlipidemia	1172751 (45.9)	38138 (35. 6)
DHH	377068 (14.8)	10169 (9.5)
Angina	265048 (10.4)	7102 (6.6)
Heart Failure	233622 (9.2)	6136 (5.7)
Peripheral Artery Disease	20582 (0.8)	518 (0.48)
AIDS	10,098 (0.4)	301 (0.3)
Connective Tissue Disease	5449 (0.2)	124 (0.1)
Rheumatoid Arthritis	60263 (2.4)	1513 (1.4)
Dementia/Alzheimers	72141 (2.8)	2194 (2.1)
Multiple Sclerosis	22323 (0.9)	616 (0.6)
Parkinson's	3151 (0.12)	85 (0.08)
Stroke	74059 (2.9)	2032 (1.9)

Cancer	210188 (8.2)	5982 (5.6)
Glaucoma	61271 (2.4)	1748 (1.6)
Depression	439763 (17.2)	13349 (12.5)
Alcohol Abuse	97748 (3.8)	3216(3)
Asthma	481873 (18.9)	14874 (13.9)
COPD	113517 (4.4)	3118 (2.9)
Chronic Kidney Disease	241422 (9.5)	6374 (6)

CHAPTER 3: Quantifying the Effects of Increased Digital Health Technology Use on Racial/Ethnic Disparities in selected Outcomes Amongst High Need Patients

Introduction

While digital health technology (specifically telemedicine and patient portals) access and use has trended upwards throughout the past couple decades, the COVID-19 pandemic greatly accelerated these trends (11, 17, 20, 101-106). Telemedicine, defined as two-way real-time virtual communication between patient and provider, offers a potential alternative to in-person care for certain types of visits. Patient portals, online applications where patients can view information, address health needs, and interact with providers, also helps bridge the care continuum.

Indeed, access to these technologies has been tied to improvements in health care utilization and certain health outcomes (7, 18). The benefits of these technologies, however, may not be shared equally across patient groups, as selection into telemedicine and patient portal use is determined by a variety of factors. These factors include racial disparities in being offered patient portal and telemedicine use, comfort using digital technologies, and differences in technological access, amongst other reasons (7, 32, 55, 61, 99, 107-110). For this reason, racial disparities in being offered patient portal and telemedicine use, comfort using digital technologies, and differences in technological access, amongst other reasons (commonly known as the “digital divide") (6, 7, 10, 13, 15, 51, 55, 72, 82, 86, 107, 111, 112). These studies find this divide exists in use and access, but further research on health-related outcomes is needed, particularly amongst high-need patient populations (7, 77). Thus, this research focuses on two exposures, FQHC-level telemedicine use, and patient-level patient portal use, drawing data from the two unique populations used in earlier chapters.

The first cohort of patients, focusing on telemedicine use, is diagnosed with Diabetes Mellitus, and receives care from a Federally Qualified Health Center (FQHC). This data set was also used in chapter 1. People with at least one chronic condition constitute a growing proportion of American adults. As of 2018, approximately half of adults had at least 1 chronic conditions, and 27% had at least two (multimorbidity). Further, amongst subgroups, those with public insurance

constituted higher than average multimorbidity prevalence (23, 77). Patients with chronic conditions require various medications, consistent provider interaction, and self-monitoring of clinical biomarkers. Further, 30%-50% of patients with combinations of these conditions have been shown to not receive appropriate treatment and thus risk future acute health problems (25, 113). Successful chronic condition management depends on medication adherence, health-conscious decisions, and communication with health care providers. Such a population could conceivably benefit from remote care.

The second cohort, focusing on patient portal use, includes patients enrolled in a state-wide health information exchange (HIE). This is the same cohort that was analyzed in chapter 2. Within this population, we look at a full population of HIE enrollees, while also focusing specifically on patients with Diabetes. A HIE allows for patient data to move seamlessly across provider groups and health systems, facilitating the care continuum. This level of interoperability facilitates broader technology adoption. Understanding both who is using HIE supplements like patient portals and how that relates to disparities in health outcomes between patient populations is crucial to determine the structure of future HIE iterations.

Provided equal usage of these technologies, we look to understand how portal and telemedicine use is differentially associated with health outcomes by race. These questions pose important policy implications. While health systems may not need exclusively virtual care in the near-term future, understanding the relationship between increased use of digital health technologies and disparities in health outcomes allows us to better understand the potential role of virtual care going forward as well as necessary equity-driven interventions to encourage use. Thus, our research objective is to assess how use of patient portals and telemedicine usage affects racial/ethnic disparities related to quality of care and health care costs. While there are underlying differences between racial/ethnic populations that drive differences in outcomes and uses, this research aims to understand how differences in outcomes persist amongst these groups, especially after the onset of COVID-19.

Methods

Data

The two cohorts in this analysis use two distinct data sources. First, we use data from Community Care Cooperative (C3), the largest FQHC-based Medicaid Accountable Care Organization in the United States. These data contain Medicaid claims (inpatient & outpatient) and EHR data from 400,000 Massachusetts patients, providing a comprehensive view of these patients' virtual and in-person care before and after the pandemic. Further, C3 pays specific attention to addressing

care inequity, allowing us to understand the effect of these efforts compared to other 'digital divide' research. Prior research into equity-driven telemedicine FQHC initiatives has shown that these efforts benefit both patient and provider (10).

Second, we use data from CurrentCare, Rhode Island's Health Information Exchange (HIE) that is managed by the Rhode Island Quality Institute. Current Care includes approximately half of the state's nearly 1.1 million residents, including about 45 million patient encounters. In addition to inpatient and outpatient visits, CurrentCare also includes 90% of lab tests and prescription fills. Its data originate from primary care and specialty practices, community health centers, hospitals, long-term care facilities, and visiting nurse agencies. In addition to these data, CurrentCare also manages a patient portal, labeled CurrentCare for Me. While this portal doesn't allow for real-time interaction with providers, patients can view recent test results, download their medical record, and send/receive messages from providers. For this research, we have data on the total number of portal visits to each of the sub-sites within the portal.

Sample

The C3 cohort follows the same inclusion criteria as chapter 1 with two notable exceptions. We broaden our cohort to include everyone with a Type II Diabetes diagnosis, rather than including those with Diabetes, Hypertension, and Hyperlipidemia (DHH). This was done so to include a larger patient population to provide more power to these triple-difference analyses. As we are working on a larger cohort, we are enabled to use a cohort with higher FQHC engagement. This cohort requires two FQHC visits in the pre period, and two FQHC visits in the post period.

The sample is defined in the same way as it was in chapter 2 for our CurrentCare cohort.

Defining Exposure

Exposure is defined in the same way as it was in chapters 1 and 2 for our C3 and CurrentCare cohorts, respectively.

Outcomes

Utilization, cost, and clinical biomarker outcomes are defined in the same way as in the previous two chapters.

Statistical Analyses

To estimate the differential effects of telemedicine and portal use by race, we use a "triple difference" approach with linear models. For the C3 cohort, this involves examining differential changes in patient-level outcomes for patients attributed to low telemedicine (LT), medium telemedicine (MT), and high telemedicine (HT) FQHCs before vs. after rapid implementation of telehealth, comparing White, Black, and Hispanic patients. For the CurrentCare cohort, we examine changes in patient-level outcomes for patients with no use (NU), some use (SU), and high use (HU) before vs. after COVID-19 onset, comparing White, Black, and Hispanic patients. The pre/post periods for both analyses are defined as they were for their respective previous chapters.

The general functional form of the telemedicine models is depicted below in equation (1), estimating outcome Y_{ijk}:

$$(1) \quad Y_{imf} = \beta_0 + \beta_1 Post_m + \beta_2 TeleFQHC_f + \beta_3 Race_i + \beta_4 Time_j TeleFQHC_f + \beta_5 Time_m Race_i + \beta_6 TeleFQHC_f Race_i + \beta_7 Time_m TeleFQHC_f Race_i + \beta_8 X_i + \propto_m + \delta_f + \varepsilon_i$$

The general functional form of the patient portal models is depicted below in equation (2), estimating outcome Y_{ij}:

$$(2) \quad Y_{im} = \beta_0 + \beta_1 Post_m + \beta_2 Portal_i + \beta_3 Race_i + \beta_4 Time_m Portal_i + \beta_5 Time_m Race_i + \beta_6 Portal_i Race_i + \beta_7 Time_m Portal_i Race_i + \beta_8 X_i + \propto_m + \varepsilon_i$$

$Time_j$ represents an observation occurring in period either before or after rapid implementation. $TechUser_k$ represents whether the observation is either a regular or irregular technology user (portals or telemedicine, depending on the cohort). $Race_i$ represents whether the observation identifies as White, Black or Hispanic. The covariate of interest (β_7) estimates the effect of being a Black patient this is a user of the relevant health technology, after COVID-19 onset. The remaining specifications resemble those from the prior two chapters. For our portal analyses, we only include models using inverse probability weights based on available baseline demographic data. We use different weights to Chapter 2, removing race from the model as it directly pertains to our outcomes of interest.

While a triple-difference model seeks to identify the difference between two difference-in-difference models, two separate parallel trends models are not required. Instead, one needs for the relative outcomes of the identifying groups who received treatment to trend in the same direction as the relative outcomes of the identifying groups in the control group prior to the exogenous shock (114). Taken within the context of this research, this requires the relative outcome trends between White and Black portal users to align with the relative outcome trends between White and Black non portal users before COVID-19 onset. To address this, we will show unadjusted outcome figures to demonstrate that these statements hold. The satisfaction of other assumptions (consistency, exogeniety, and positivity) was discussed in previous chapters, and the same logic holds for this chapter.

Results

C3 Cohort

The demographics for our C3 cohort are displayed in Table 3.1 by treatment category. With the slightly revised inclusion criteria, we include 216,125 patient-month observations from 5,509 beneficiaries. These observations come from 16 FQHCs, which are divided into the same treatment groups as chapter 1, LT, MT, and HT. After confirming the relative telemedicine proportions remained consistent, we kept FQHCs in the same treatment groups as they were in for chapter 1. To reference these, please see Table A1 and Figure A1 in chapter 1's appendix. Approximately 86% of observations stem from patients attributed to a MT FQHC. THE LT and HT groups comprise 8% of 6% of observations, respectively. Across the three treatment groups, age is relatively consistent. HT observations are the most likely to be male. MT observations are most likely to be female, Hispanic, Spanish speaking, and be have been diagnosed with a stroke and heart failure. LT observations are most likely to be White, English speaking, and be diagnosed with any chronic condition. To see these demographics aggregated over all treatment groups, please see Table 3.A1 in the appendix.

Figures 1 and 2 resemble those of chapter 1. Figure 3.1 illustrates how FQHC visits trend over time, by modality and race. We can observe how total visits do not appear to be significantly affected by COVID-19 onset, with virtual visits substituting the decline in in-person visits. While in-person visits do not return to pre-pandemic levels, the persistence of telemedicine visits continues through the end of 2021. When comparing across race/ethnicity lines, we observe that Black and White diabetic patients observe similar FQHC utilization prior to the pandemic. Hispanic patients observe a similar

trend, but at lower levels than Black and white patients. These trends appear to lessen after COVID onset, due to equal levels of observed in-person visits. While the overall difference in total visits remains, it appears smaller than it was prior to the pandemic.

Figure 3.2 shows the same trends in FQHC visits, but by treatment group. Similar to chapter 1, we observe that pre-period utilization levels are largely consistent across treatment groups. After March 2020, we see HT total visits increase, while LT total visits fall and MT visits remain consistent. To see how these visits breakdown by modality, please see Figure 3.A1. LT patients resume in-person care quicker than MT and HT patients, who use telemedicine as the dominant modality through the final months of 2021.

Given the levels of treatment and the multiple levels of race/ethnicity, we split up our unadjusted outcome figures to show White and Black comparisons and White and Hispanic comparisons separately. Similar to chapter 1, we show these for each outcome related to care utilization, costs, biomarkers, and Healthcare Effectiveness Data and Information Set (HEDIS) measures. The appendix displays each of these figures. Figures 3.A2a-3.A2t show the White-Black comparisons. We include two sets of cost figures, with one excluding the LT – Black cohort due to extreme values skewing the scale. Figures 3.A3a-3.A3o show White-Hispanic comparisons. We can see that while there appears to be noise in some of the cost and biomarker estimates, the relative trends in White and Black/Hispanic treated outcomes and White and Black/Hispanic control outcomes in the absence of treatment suggest the validity of the triple-difference parallel trends assumption.

To view the regression estimates interest for our models, please see Tables 3-4. Due to the volume of models, we only include those with significant estimates in the body of the chapter. All models can be seen in the appendix. Table 3.3 focuses on White:Black Disparities. We observe that the only significant estimate stems from the model estimating Professional Outpatient Costs at the 90% level (CI: [-3470,256], p-value=0.091).

Table 3.4 focuses on White:Hispanic Disparities. Hispanic patients served by FQHCs with higher telemedicine use see 0.13 more FQHC in-person visits (MT, CI: [0.01,0.24], p-value=0.028), 1.01 fewer non-FQHC outpatient visits (HT, CI: [-1.98,-0.05], p-value=0.028), 0.61 higher HbA1c (MT, CI: [0.22,1], p-value=0.002), and increased probability of poor blood glucose control (MT (0.09), CI: [0.02,0.17], p-value=0.014, HT (0.11, 90%), CI: [-0.01,0.23], p-value=0.074)

compared to their control observations in comparison to White treated observations did compared to their control observations.

Current Care Cohort

The demographics of our patient population are displayed in Table 3.5 by treatment group. This sample includes 2,040,947 patient-month observations, coming from 84,240 patients. Approximately 83% of observations originate from our control group, those who had never used a patient portal. Observations from 'some use' (SU) patients comprise 10%, and 'high use' (HU) patients make up the remaining 7%. While most patients have not used the portal, the mean number of portal visits is 5.8. Further, we observe that portal users are, on average, younger, healthier, more likely to be White, identify as female, less likely to experience homelessness and reside in a '028' area code. Table 3.A2 displays these demographics unrelated to treatment status.

Figures 5a and 5b better visualize the relationship between portal use and age. Figure 3.3a focuses on the full sample, showing how portal use changes with age. While each race/ethnicity sees declining portal use with age, White CurrentCare members see higher use across all ages. Further, the rate of decline as observations move across the age continuum is less severe for White patients. When focusing only on portal users (Figure 3.3b), we see similar interracial relationships. Both Black and Hispanic portal use is lower than that of White portal users for young CurrentCare for Me users. Black and Hispanic use appears to decline more severely as you focus on older portal users than it does for White patients. Indeed, amongst portal users, White users appears consistent across the age range.

To understand how unadjusted outcomes trend across time, we created plots charting each utilization outcome (Figures 3.A4a-3.A4i for Black-White comparisons and 3.A5a-3.A5i for Hispanic-White comparisons). To satisfy the triple-difference assumptions described previously, the collective movement of the red and green lines must correspond to the collective movements of the blue lines. When applying this test to the utilization outcomes, we largely come to the conclusion that this assumption is satisfied. The only outcome which appears to potentially violate this assumption is lab encounters. Thus, we will focus on regression estimates for all outcomes except for lab encounters. Given the noisy nature of some of these outcomes, we provide some lagged figures in the appendix to reinforce the satisfied pre-trends assumption (Figures 3.A6a-3.A6r). In these figures, each point is the average value of the current month and the 4 preceding months.

Table 3.6 displays all White:Black models that yield a statistically significant estimate. Black portal users see 0.35 fewer total visits (SU, CI: [-0.62,-0.08], p-value=0.011), fewer outpatient visits (SU, CI: [-0.936,-0.02], p-value=0.028), 0.18 fewer lab visits (-0.18 (SU), CI: [-0.29,-0.07], p-value=0.002, -0.14 (HU), CI: [-0.25,-0.02], p-value=0.021), 2.69 lower Diastolic BP (SU, CI: [-5.16,-0.22], p-value=0.033) and 9.18 lower LDL (90% significance, CI: [-18.8,0.45], p-value=0.062) compared to their control observations in comparison to White treated observations did compared to their control observations.

The White:Hispanic parameters of interest can be seen in Table 3.7 for models that yield significant estimates. Hispanic portal users see 2.53 higher Diastolic BP (CI: [0.95,4.1], p-value=0.002) compared to their control observations in comparison to White treated observations did compared to their control observations.

Discussion

Collectively, these analyses suggest that differential effects of health technology use exist in certain scenarios, and more research is needed to investigate the source of these differences. A strength of this analysis lies in the ability to examine two unique datasets from sources who have approached technology usage differently. C3 has built equitable initiatives into their care management throughout its existence, while CurrentCare hasn't pursued extensive patient portal activation from its members to this point. These differences can help us understand how racial disparities in our outcomes differ between the two studies.

Within the C3 cohort, we largely find no significant effect of FQHC-level telemedicine use on health care utilization, costs, and individual health status. Black patients appear to derive the same benefits from increased telemedicine use as White patients, which suggests that the concerted efforts to improve health equity have succeeded in the rapid implementation of telemedicine across Massachusetts Medicaid FQHCs. Based on the consistent direction of the cost estimates, there is reason to believe that costs reductions due to telemedicine are larger amongst Black telemedicine users, which would certainly help encourage broader adoption.

With our Hispanic and White patient estimates, we similarly observe largely insignificant estimates, but a couple models hold interesting implications. First, we see that total in-person FQHC visits increase for higher telemedicine-use FQHCs, while non-FQHC outpatient visits decrease. Such results suggest that while Hispanic patients of high telemedicine-use clinics have more opportunities to use telemedicine, they are leveraging in-person FQHC care at higher levels than their

White counterparts. Further, our findings suggest that Hispanic Diabetics see a significantly larger negative effect of telemedicine use on HbA1c outcomes compared to White diabetics. This is seen in both the HbA1c outcome, and in the poor Diabetes control HEDIS outcome. While HEDIS measures may be reflective of the way in-person care facilitates more successful measurement rather than actual disease management (see chapter 1), the biomarker estimate suggests these estimates have some validity.

Taken together, along with the in-person FQHC estimates, these findings may be indicative of a language-related issue. While preferred language is controlled for in these analyses, we may still be observing potential barriers to those with limited English proficiency (LEP). In-person visits may offer more available people who can translate for patients and providers who aren't comfortable speaking the same language. Telemedicine provides less of an opportunity to involve these people, especially if both patient and provider are conducting virtual visits from home. Such a finding underscores the importance of ensuring language barriers are minimized in virtual care, as they have a demonstrated effect of increasing health disparities between Hispanic and White patients (111, 115-117). Such a finding aligns with the larger need to understand the ideal scope of telemedicine (53). Ultimately, however, we largely don't observe widening racial disparities within this C3 cohort, underscoring the importance of equity-driven care strategies.

These takeaways can be extended into our analyses with the CurrentCare cohort. Each model supports the assertion that all patients saw increased health care utilization after the onset of COVID-19. This can be attributed to the emergence of COVID-related care, coupled with the ability to transition some previous in-person care to virtual care. As was observed in chapter 1, total utilization increasing after in-person care largely resumes occurs due to the persistent influence of virtual care. Focusing on Hispanic-White differences, however, we see that portal users after COVID-19 onset are associated with larger negative effects on Diastolic BP for Hispanic patients than for White patients. Such findings could originate from similar barriers that affected C3 patients. Those who may need to rely more on portals but aren't comfortable in the provided language may miss key information about their health and care management (111). While most outcomes do not suggest disparities in outcomes between White and Hispanic patients, it is important to make sure use is incentivized for Spanish-speakers. CurrentCare continues to invest time and resources in making the portal multi-lingual, which will likely lower some of these barriers. Additional translation capabilities may also be necessary for free-text spaces, as this is important for direct patient-provider communication.

Focusing on Black-White disparities also yield important findings. Black portal users appear to see lower health care utilization and lower biomarker measurements than White portal users, compared to their respective controls. While we don't know the nature of this care, the fact that it does not correspond to widening disparities in downstream outcomes suggests that some of this care may be substituted for portal use. In a vacuum, it is promising that Black patients (especially those with chronic conditions) potentially see a larger benefit from patient portals than White patients after an exogenous shock encouraging portal use. Portals can increase access by lowering obstacles like transportation and needing to work around strict work schedules (7, 118). Such obstacles are likely to disproportionately affect underserved communities (98, 119). The issue, however, resides in the fact that portal use is still more common amongst White patients. While Black patients comprise 8.5% of the non-portal users in the sample, they only comprise roughly 3.5% of the SU treatment group. A lower proportion of black patients use portals for a variety of socioeconomic and cultural reasons, including lower internet access, a lower likelihood of being offered use, and less confidence in data safety (60, 61). Regardless of the underlying determinants, lower portal use signifies unrealized health improvements that are larger in magnitude than those for portal-using White patients. The culmination of these models suggests potential widening racial disparities in total health care utilization, and health more generally (the 'digital divide').

Prior research has demonstrated that portal users see fewer outpatient, ED visits and preventable hospitalizations than their non-portal using peers (81, 91-93). Such trends could be due to portal users being able to substitute portal use for certain in-person conversations (94). Fortunately, these models do not show an effect of widening disparities in downstream health care utilization, suggesting that any disparities in care engagement haven't resulted in differences in ED or inpatient visits. Our biomarker models largely yield statistically insignificant results, and the few results that are significant do not appear to have a tangible clinical effect. This, taken with the downstream utilization models, suggest that any disparities in care engagement do not translate to disparities in health. While encouraging, continued analyses may be necessary to identify significant estimates from data with a longer time horizon and more observations.

Pandemic onset necessitated a near-universal increase in virtual health care, from telemedicine visits to patient portal use. When in-person care becomes too risky, these technologies serve a potentially helpful role, as found in previous research (6-8, 51, 85, 117). The findings of this research extend those conclusions, while illustrating that various racial groups may experience telemedicine and portals differently. These varying responses by Black and Hispanic patients in relation to White patients are likely driven by different barriers to in-person and virtual care. Where Black patients may benefit from

being able to leverage virtual care with adequate outreach and training, Hispanic patients may need more help, particularly as it pertains to overcoming language barriers. Further, organizations that have either been considering health equity directly or those that aim to do so going forward should continue to evaluate how their care processes potentially contribute to a widening 'digital divide'.

While telemedicine and portal use are not exclusive determinants in widening disparities, they facilitate easier access to many of the mechanisms that directly influence health, including care management, healthy decision-making, and medication adherence (84, 88). To ensure more equitable outcomes, additional work is necessary. Specific outreach is required to encourage use for underserved groups, particularly those with chronic conditions (7, 60, 88, 120). Issues arise with the costs involved with these tailored efforts. Providers who work in underserved communities are willing to work with patients on feeling comfortable with these technologies, but they are also likely to bear a large share of the burden when it comes to educating and training patients (7). Thus, it is important for policymakers to allocate sufficient resources towards both improving technology use amongst marginalized communities, but also towards supporting providers in charge of providing ongoing care.

In the case of our telemedicine research, the largely null effects of care engagement, utilization, and costs suggests telemedicine is a cost-effective alternative to certain types of in-person care. Continued research should be done to identify the types of care that can be performed remotely, and how to ensure this shift doesn't have unintended consequences. Additional analyses incorporating the indirect costs of telemedicine (including hardware, software, and training) will be valuable in getting a better picture of the funding required to support the rise in virtual care.

There are limitations with this research. As mentioned in chapter 1, the size of the data set limits power, potentially obscuring true causal relationships. As mentioned in chapter 2, while the portal data can offer keen insights, the structure of the data set limits causal interpretation. Similar to both previous chapters, there exists the potential for unobserved confounding. Further, our single-state analyses may limit external validity. Finally, as we get further from COVID-19 onset, we may better understand telemedicine and portals' effects on long-run health and care engagement, and data incorporating the longer post periods will prove useful.

Despite these limitations, this work suggests that different racial groups derive different levels of benefit from patient portal and telemedicine use.

Conclusion

As COVID-19 shifted patient care to virtual modalities, we see some differential effects by race and ethnicity. In a diabetic cohort that receives care from an equity-driven Medicaid ACO, we largely see no differential effects of receiving care from a FQHC that uses telemedicine at higher rates. A potential exception exists between White and Hispanic telemedicine users, the latter of which may suffer from language barriers that can be reinforced with virtual care. Within a cohort of HIE members, we see that Black patients may derive more benefit from patient portals, but use them at lower levels. Hispanic portal users also may see more positive outcomes than white patients, but language-related issues may create barriers.

Taken together, we can conclude that providers and policymakers must continue to consider how different groups of people interact with these technologies and how that influences ongoing care management. It is important to ensure equity in health technologies' access and use by instituting programs that encourage increased used by underserved communities, particularly as virtual visits continues to constitute a significant portion of administered care.

Tables and Figures

Table 3.1: Demographics by Treatment Group

Demographic	**Low (n=18,012)**	**Medium (n =185,897)**	**High (n =12,216)**
Mean Age (SD)	49.5 (10.2)	50.6 (10.2)	50.2 (9.9)
Sex, N (%)			
Female	10330 (57.4)	113238 (60.9)	5346 (43.8)
Male	7682 (42.7)	72659 (39.1)	6870 (56.2)
Race, N (%)			
White, NH	9794 (54.4)	45876 (24.7)	5890 (48.2)
Black, NH	938 (5.2)	37520 (20.2)	1257 (10.3)
Hispanic, any race	7280 (40.4)	102501 (55.1)	5069 (41.5)
Primary Language, N (%)			
English	10498 (59)	68346 (38.5)	6113 (52.3)
Spanish	3633 (20.4)	69391 (39.1)	3247 (27.8)
Other Language	0	46 (0.03)	0
Unknown	3671 (20.6)	39573 (22.3)	2322 (19.9)
Top 5 Zipcodes, Zip (%)			
	01420 (36.3)	01040 (8.7)	01970 (30.5)
	01453 (15.3)	01902 (7.7)	01960 (16.1)
	01440 (11)	02301 (7.1)	01930 (12.9)
	01301 (6.4)	02128 (4.3)	01915 (6.6)
	01364 (4.6)	01610 (4.3)	01902 (4.8)
Condition, N (%)			
Mental Health History	14602 (81.1)	140512 (75.6)	9001 (73.7)

Substance Use History	9172 (50.9)	74287 (40)	5211 (42.7)
Asthma	6338 (35.2)	59157 (31.8)	2921 (23.9)
COPD	4516 (25.1)	36614 (19.7)	1917 (15.7)
Cardiovascular Disease	4677 (26)	46806 (25.2)	2688 (22)
Ischemic Heart Disease	3343 (18.6)	32578 (17.5)	1886 (15.4)
Myocardial Infarction	609 (3.4)	8202 (4.4)	557 (4.6)
Atrial Fibrillation	684 (3.8)	6996 (3.8)	508 (4.2)
Cerebral Vascular Incident	1117 (6.2)	13178 (7.1)	677 (5.5)
Heart Failure	1393 (7.7)	14726 (7.9)	805 (6.6)
Hypertension	13917 (77.3)	139153 (74.9)	9415 (77.1)
Hyperlipidemia	10639 (59.1)	84385 (45.4)	4083 (33.4)

Note: Each categorical variable (except for Atrial Fibrillation) is associated with FQHC category (95% level)

Figure 3.1: FQHC Use by Race over Time

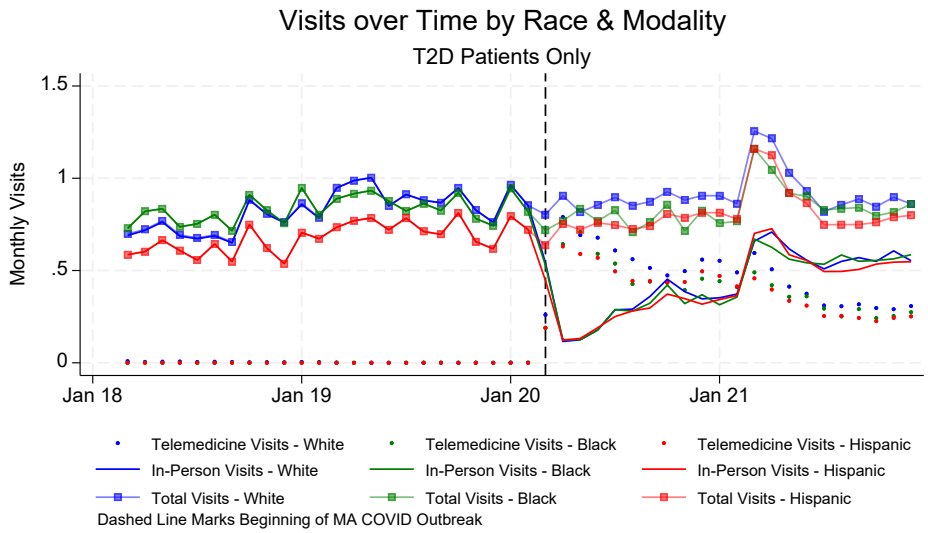


Figure 3.2: FQHC Use by Treatment Group over Time

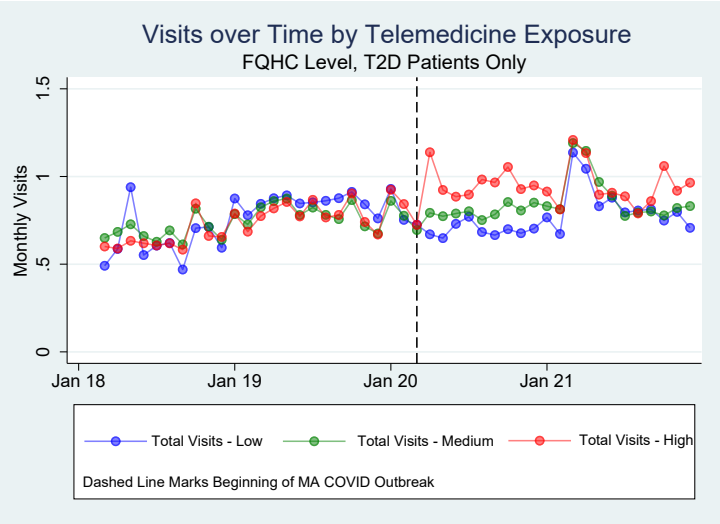


Table 3.3: Significant Regression Coefficients (C3, White:Black)

		White						Black								
		LT		MT		HT		LT		MT		HT		LT:MT		
	N	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DDD	95% CI, p-value
Professional Outpatient Costs	*70652*	1284	1661	1234	1557	-	-	1064	2995	1149	1310	-	-	-1716.00	**-1607***	(-3470,256), 0.091

**= Significant at 95% level, *=Significant at 90% level

Table 3.4: Significant Regression Coefficients (C3, White:Hispanic)

		White						Hispanic											
		LT		MT		HT		LT		MT		HT		LT:MT			LT:HT		
	N	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DDD	95% CI, p-value	Unadjusted DiD	Adjusted DDD	95% CI, p-value
FQHC In-Person Visits	*176410*	0.81	0.5	0.85	0.44	-	-	0.87	0.55	0.68	0.41	-	-	0.15	**0.13****	(0.01,0.24), 0.028	-	-	
Non-FQHC Outpatient Visits	*176410*	4.5	4.95	-	-	4.85	5.73	3.92	4.39	-	-	1.64	1.84	-	-	-	-0.70	**-1.01****	(-1.98,-0.05), 0.04
HbA1c	*18436*	7.58	7.71	7.78	7.86	-	-	8	7.66	7.88	8.04	-	-	0.55	**0.61****	(0.22,1), 0.002	-	-	-
Poor HbA1c Control	*129919*	0.3	0.39	0.33	0.37	0.42	0.44	0.39	0.43	0.35	0.4	0.36	0.44	0.06	**0.09****	(0.02,0.17), 0.014	0.11	**0.11***	(-0.01,0.23), 0.074

**= Significant at 95% level, *=Significant at 90% level

Table 3.5: CurrentCare Demographics by Treatment Group

By Levels of Portal Use	**No Use**	**Some Use**	**High Use**
Observation Level	*N=1,692,197*	*N = 204,382*	*N = 144,368*
Mean Portal Visits (SD)	0 (0)	6.1 (3.8)	90.1 (199)
Mean Age (SD)	59.3 (16.4)	54 (15.7)	53.1 (15.6)
Female (%)	1078535 (63.7)	145118 (71)	105869 (73.3)
Race (%)			
White	1452472 (85.8)	190164 (93)	137086 (95)
Black	131673 (7.8)	7006 (3.4)	3594 (2.5)
Hispanic	108052 (6.4)	7212 (3.5)	3688 (2.6)
3-Digit Zip: 029 (%)	552747 (32.7)	57883 (28.3)	42644 (29.5)
Unhoused	24079 (1.4)	710 (0.4)	664 (0.5)
Diabetes	362209 (21.4)	31448 (15.4)	19309 (13.4)
Hypertension	960458 (56.8)	90810 (44.4)	61407 (42.5)
Hyperlipidemia	804369 (47.5)	79580 (38.9)	54694 (37.9)
DHH	260760 (15.4)	19986 (9.8)	13153 (9.1)
Angina	193731 (11.5)	14614 (7.2)	10898 (7.6)
Heart Failure	171441 (10.1)	9873 (4.8)	7323 (5.1)
Peripheral Artery Disease	16061 (1)	1188 (0.6)	709 (0.5)
AIDS	6784 (0.4)	688 (0.3)	390 (0.3)
Connective Tissue Disease	3475 (0.2)	588 (0.3)	124 (0.1)
Rheumatoid Arthritis	40925 (2.4)	3737 (1.8)	3396 (2.4)
Dementia/Alzheimers	49794 (2.9)	2998 (1.5)	1969 (1.4)
Multiple Sclerosis	14943 (0.9)	2134 (1)	1986 (1.4)
Parkinson's	2240 (0.1)	151 (0.1)	105 (0.1)

Stroke	51167 (3)	3852 (1.9)	2671 (1.9)
Cancer	152354 (9)	14232 (7)	10718 (7.4)
Glaucoma	41215 (2.4)	3722 (1.8)	2280 (1.6)
Depression	290715 (17.2)	32109 (15.7)	22454 (15.6)
Alcohol Abuse	70128 (4.1)	3626 (1.8)	3011 (2.1)
Asthma	317939 (18.8)	35572 (17.4)	26870 (18.6)
COPD	86303 (5.1)	4364 (2.1)	3839 (2.7)
Chronic Kidney Disease	172863 (10.2)	13075 (6.4)	9122 (6.3)

Note: Each categorical variable is associated with FQHC category (95% level)

Figures 3a and 3b: Portal Use by Age and Race

Figure 3.3a: Full Sample

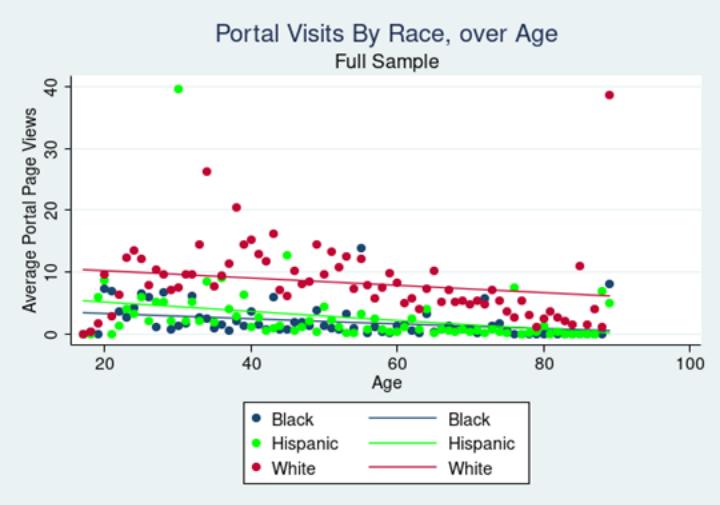


Figure 3.3b: Portal Users only

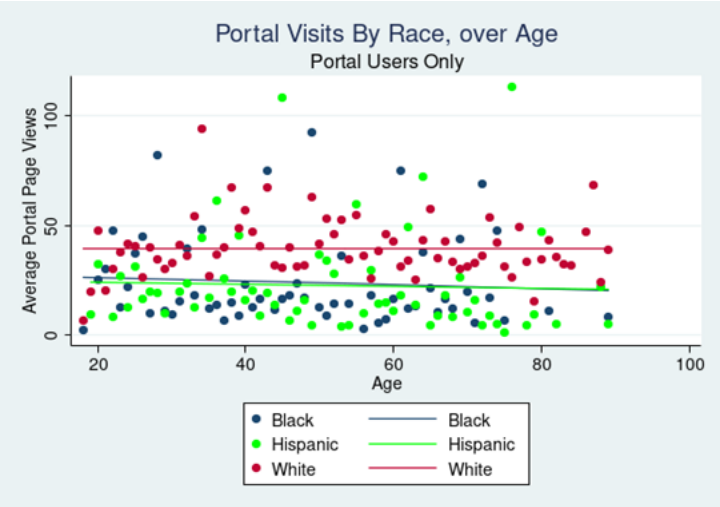


Table 3.6: Significant Regression Coefficients (CurrentCare, White:Black)

		White						Black						NU:SU			NU:HU		
		NU		SU		HU		NU		SU		HU							
	N	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Unadjusted DiD	Adjusted DDD	95% CI, p-value	Unadjusted DiD	Adjusted DDD	95% CI, p-value
Total Visits	*1766231*	2.72	3.10	2.60	2.88	-	-	2.89	3.49	2.78	3.11	-	-	-0.17	**-0.35****	(-0.62,-0.08), 0.011	-	-	-
Outpatient Visits	*1766231*	1.5	1.73	1.61	1.69	-	-	1.66	1.98	1.64	1.79	-	-	-0.02	**-0.19****	(-0.36,-0.02), 0.028	-	-	-
Lab Visits	*1766231*	1.01	1.13	0.85	1.06	0.88	1.11	0.92	1.17	0.9	1.08	0.99	1.1	-0.16	**-0.18****	(-0.29,-0.07), 0.002	**-0.25**	**-0.14****	(-0.25,-0.02), 0.021
Diastolic BP	*127760*	76.9	76.3	78.1	77.2	-	-	79.5	80.2	80.7	79.1	-	-	-2.00	**-2.69****	(-5.16,-0.22), 0.033	-	-	-
LDL	*161309*	96.4	91.7	99.5	96.6	-	-	98.1	97.5	114	104	-	-	-11.20	**-9.18***	(-18.8,0.45), 0.062			

**= Significant at 95% level, *=Significant at 90% level

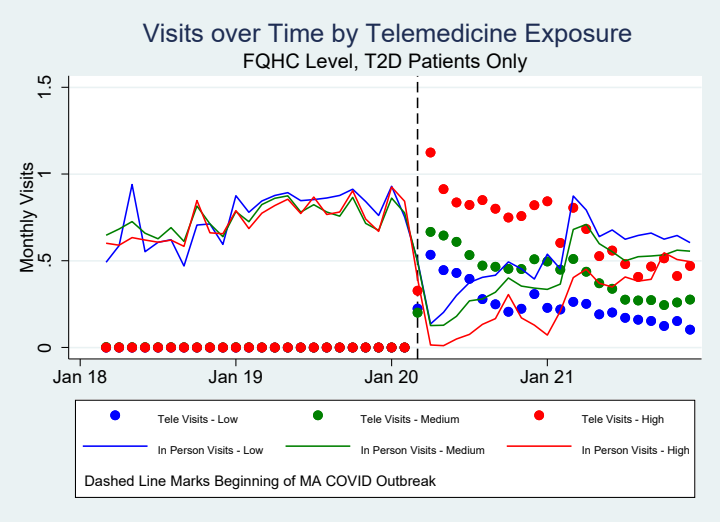
Table 3.7: Significant Regression Coefficients (CurrentCare, White Hispanic)

		White						Hispanic								
		NU		HU				NU		HU				NU:HU		
	N	Pre	Post	Pre	Post			Pre	Post	Pre	Post			Unadjusted DiD	Adjusted DDD	95% CI, p-value
Diastolic BP	*120637*	76.9	76.3	77.5	77.1	-	-	77.8	78.1	78	78.7	-	-	0.20	**2.53****	(0.95,4.10), 0.002

**= Significant at 95% level, *=Significant at 90% level

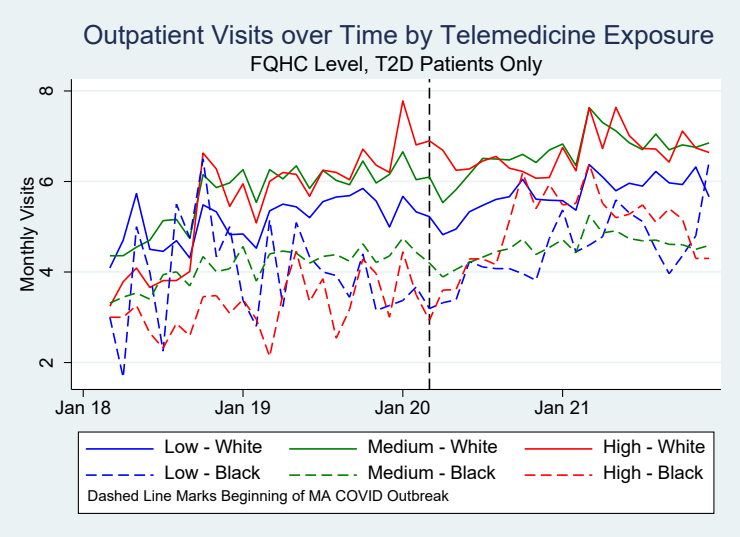
Appendix: Table and Figures:

Figure 3.A1: Visits by Modality and Telemedicine Category



Figures 3.A2a-3.A2t: Un-adjusted outcome trends (White – Black)

A2a: Outpatient Visits



A2b: Outpatient (Non-FQHC) Visits

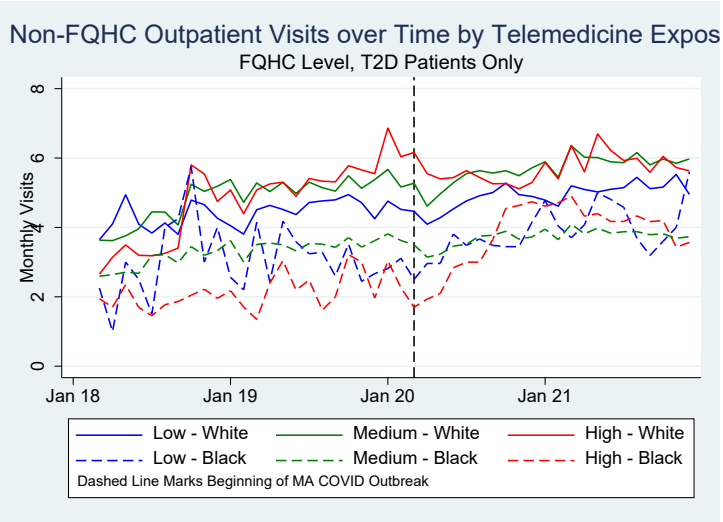


Figure A2c: Emergency Department Visits

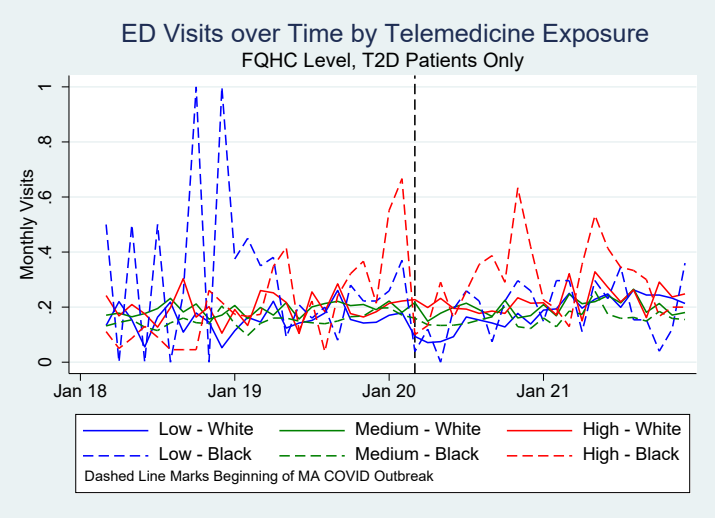


Figure A2d: Inpatient Visits

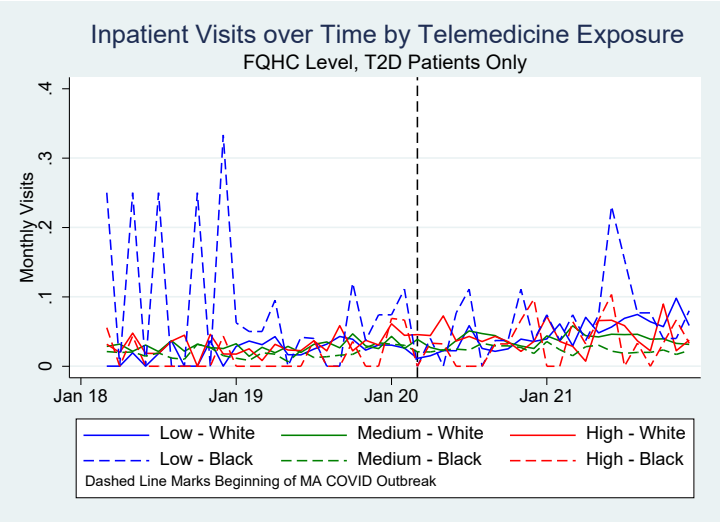


Figure A2e: Outpatient Costs

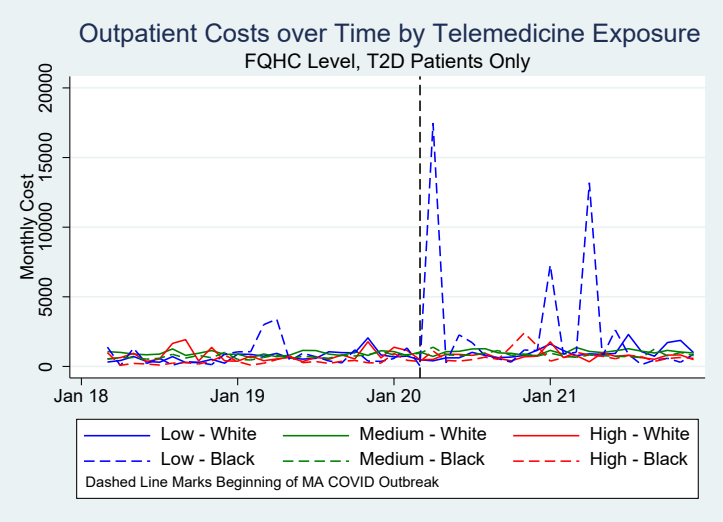


Figure A2f: Outpatient Costs (Without Low – Black)

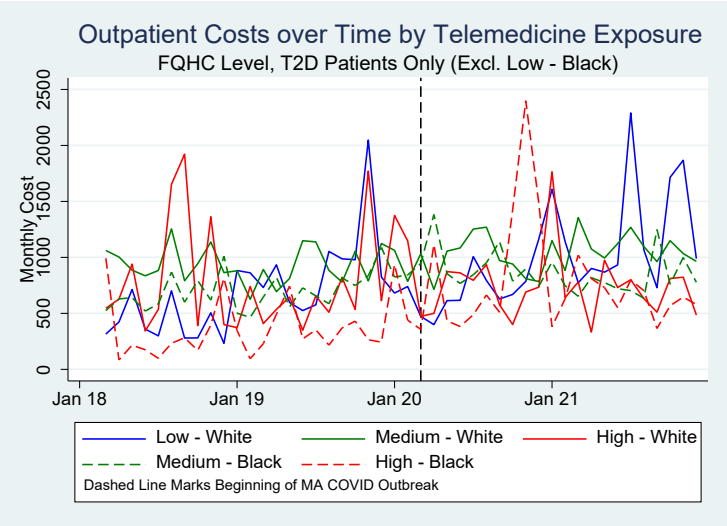


Figure A2g: Other Outpatient Costs

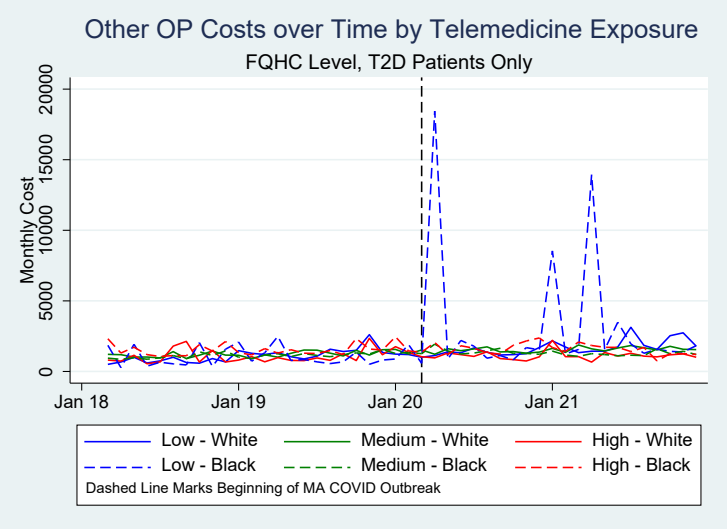


Figure A2h: Other Outpatient Costs (Without Low – Black)

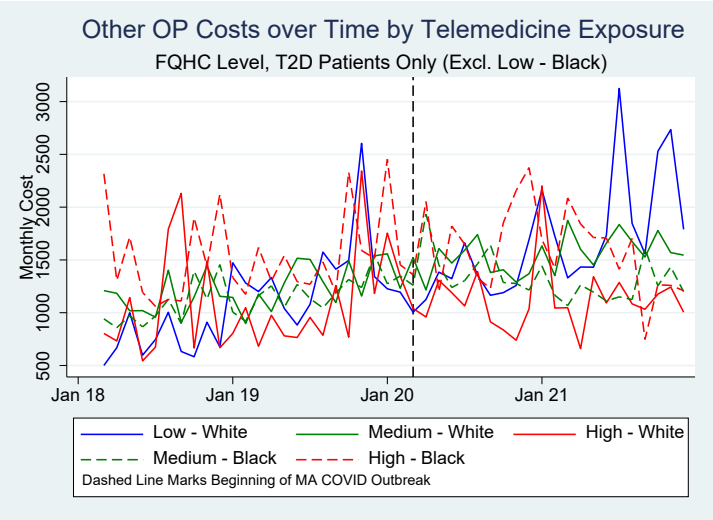


Figure A2i: Emergency Department Costs

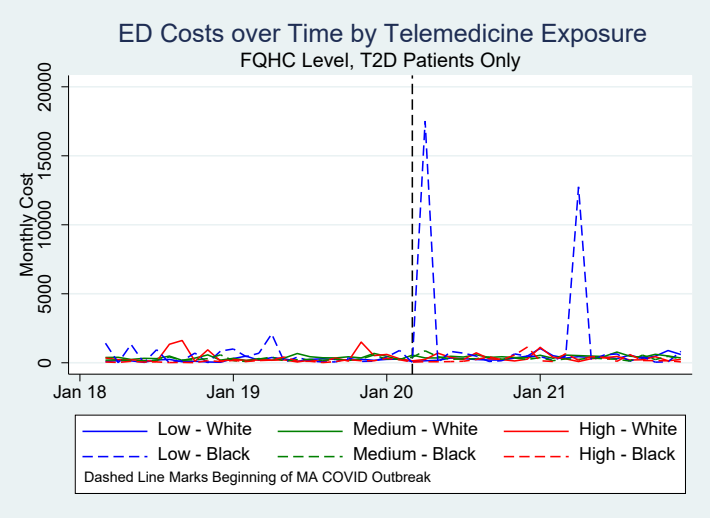


Figure A2j: Emergency Department Costs (Without Low – Black)

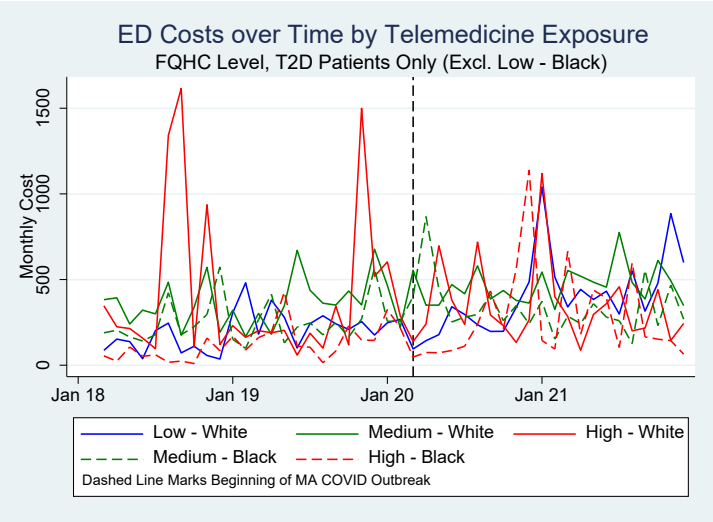


Figure A2k: Inpatient Costs

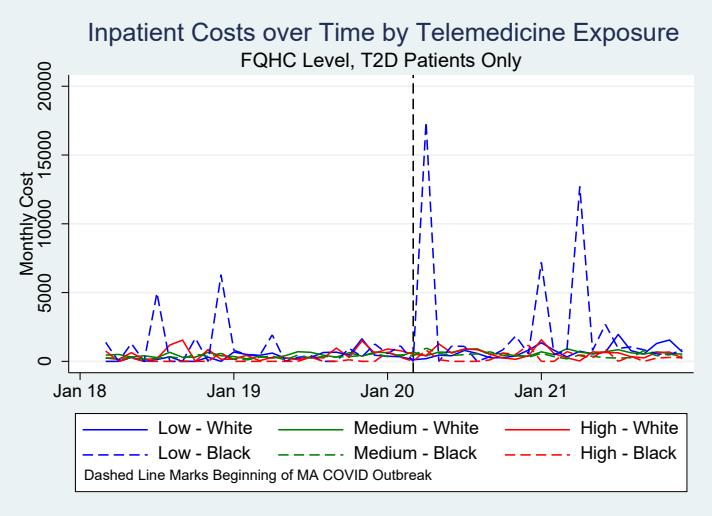


Figure A2l: Inpatient Costs (Without Low – Black)

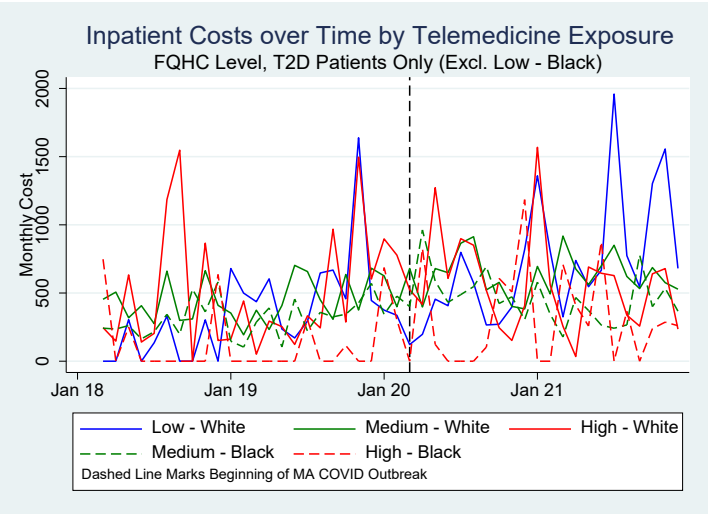


Figure A2m: Total Costs

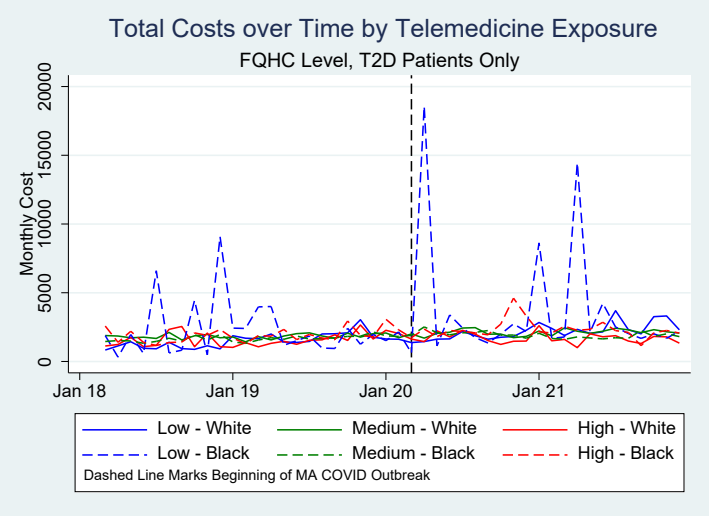


Figure A2n: Total Costs (Without Low – Black)

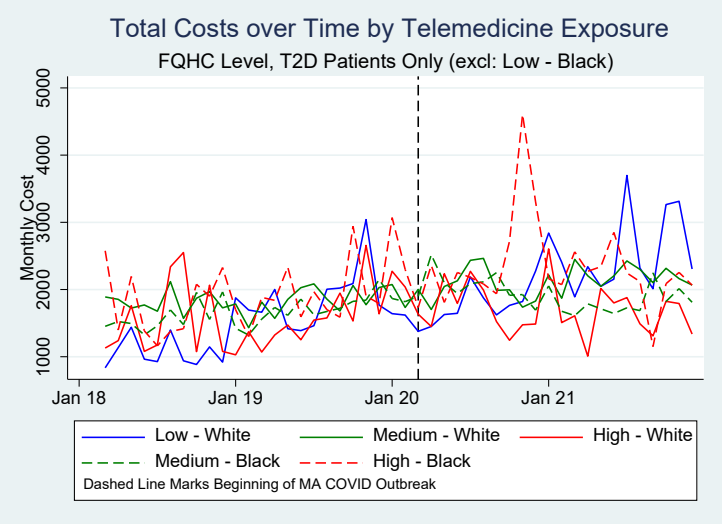


Figure A2o: Systolic BP

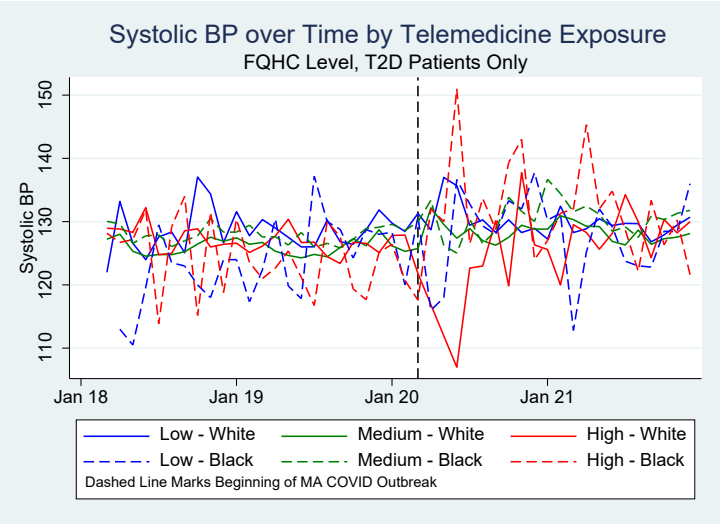


Figure A2p: Diastolic BP

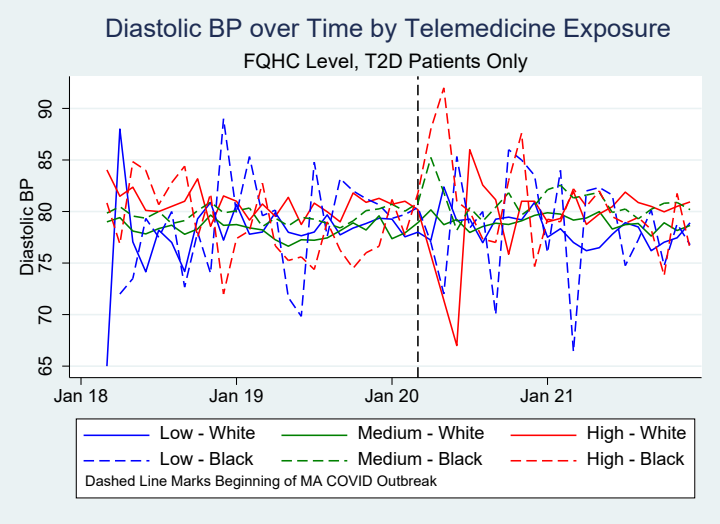


Figure A2q: Blood Glucose

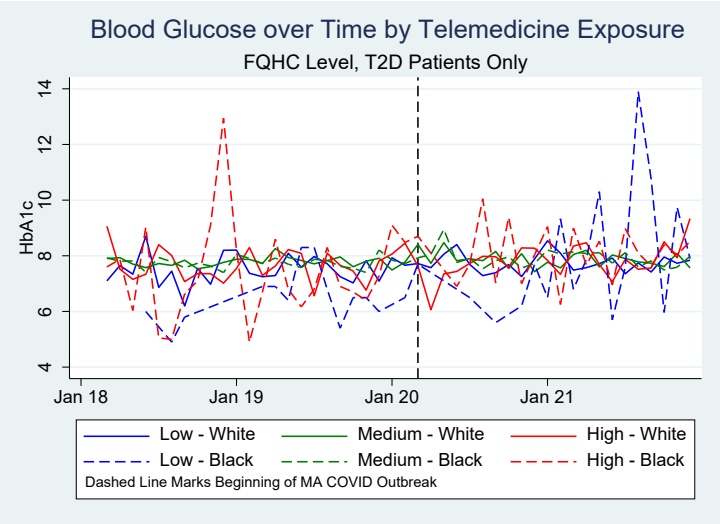


Figure A2r: Retina Exam Rates

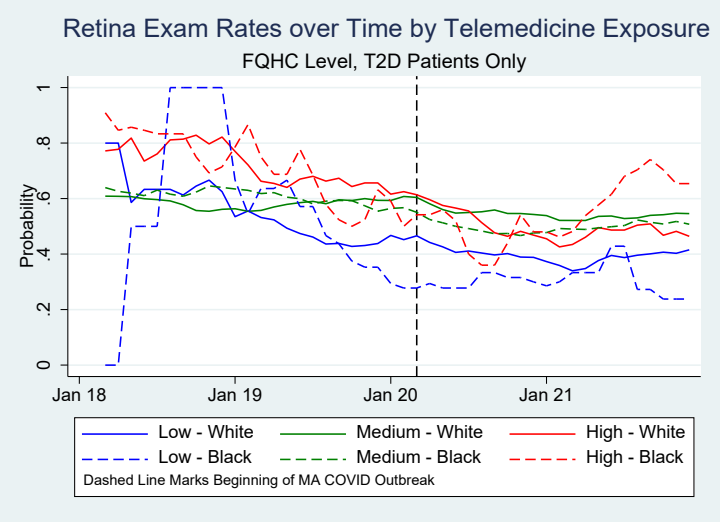


Figure A2s: Blood Pressure Control Rates

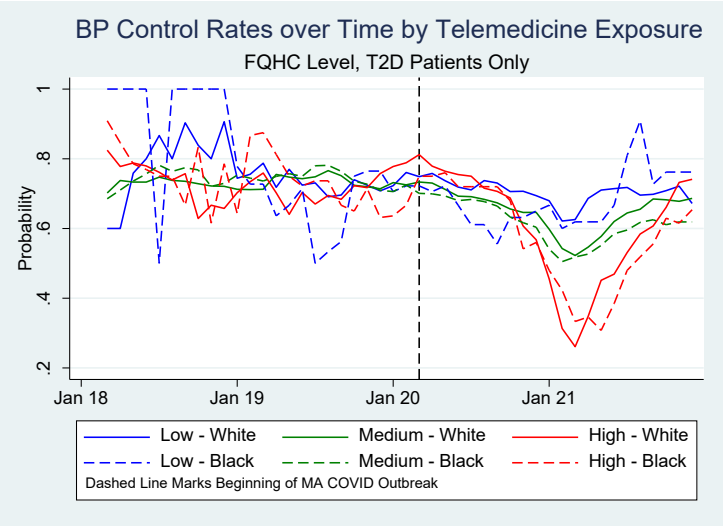
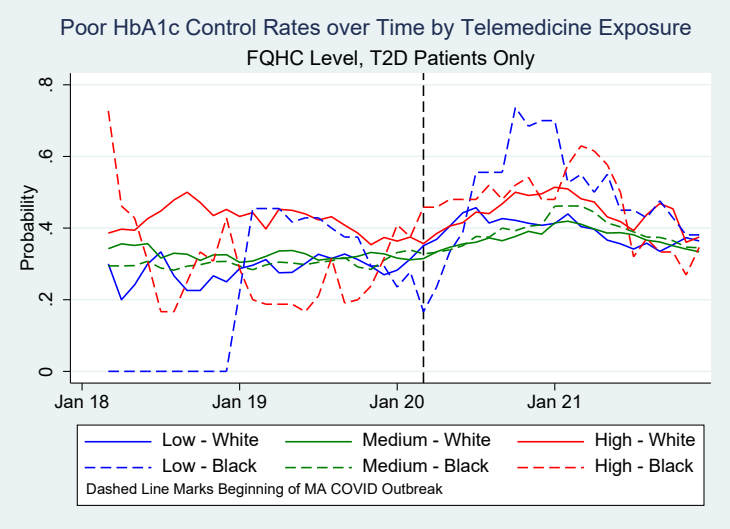


Figure A2t: Poor Blood Glucose Control Rates



Figures 3.A3a-3.A3o: Un-adjusted Outcome Trends (White – Hispanic)

Figure A3a: Outpatient Visits

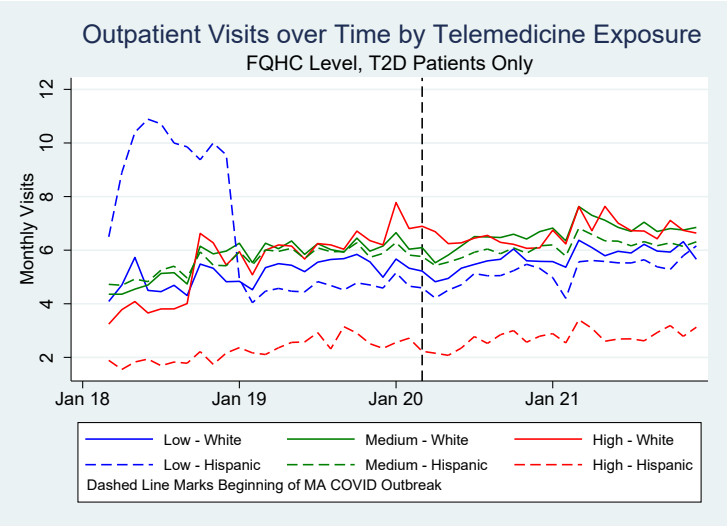


Figure A3b: Outpatient (non-FQHC) Visits

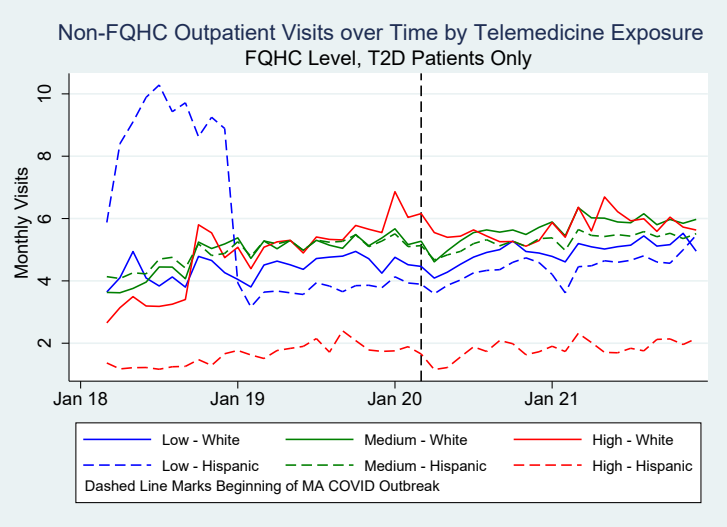


Figure A3c: Emergency Department Visits

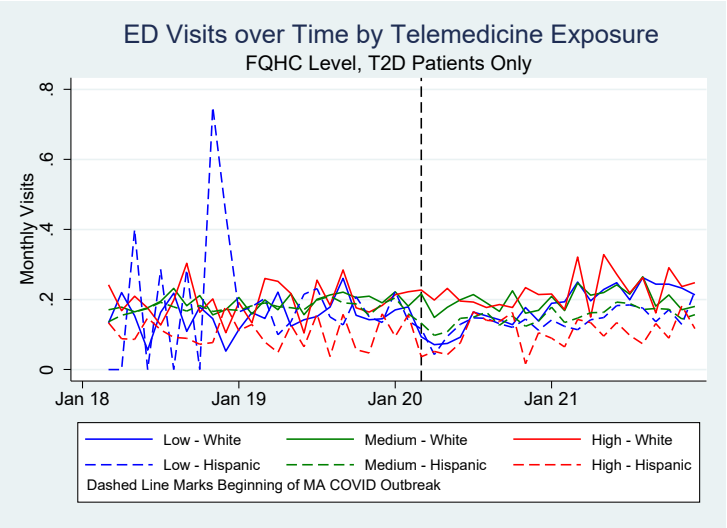


Figure A3d: Inpatient Visits

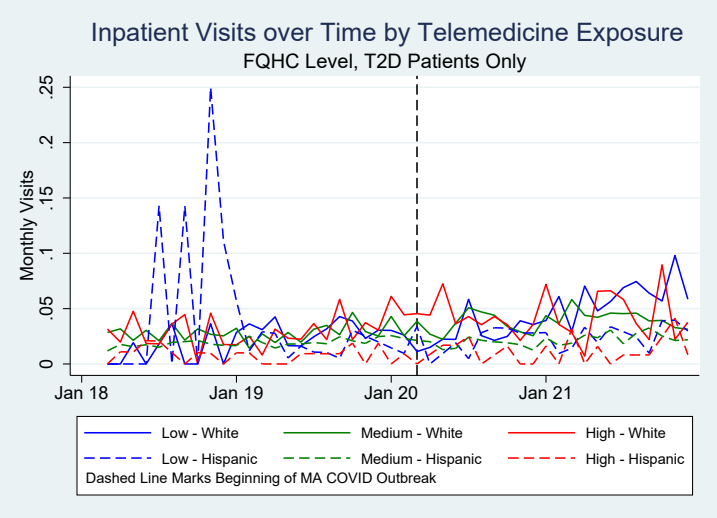


Figure A3e: Outpatient Costs

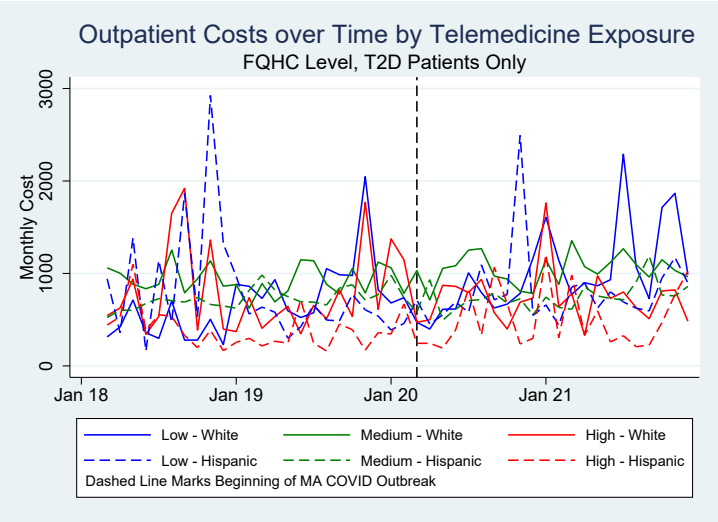


Figure A3f: Outpatient (Other) Costs

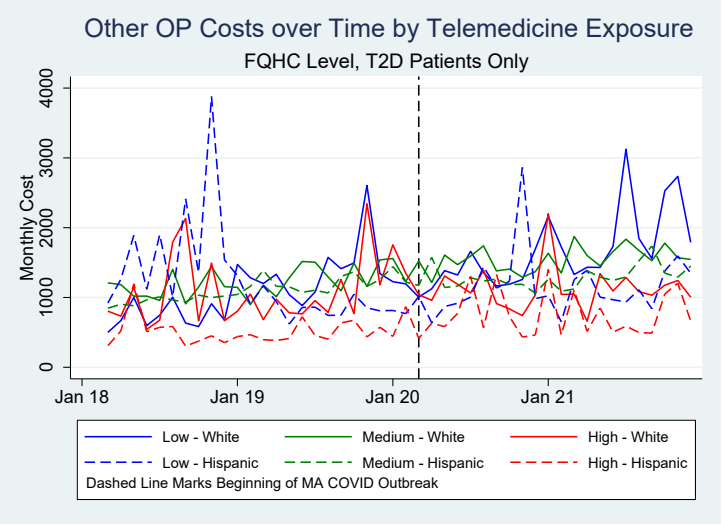


Figure A3g: Emergency Department Costs

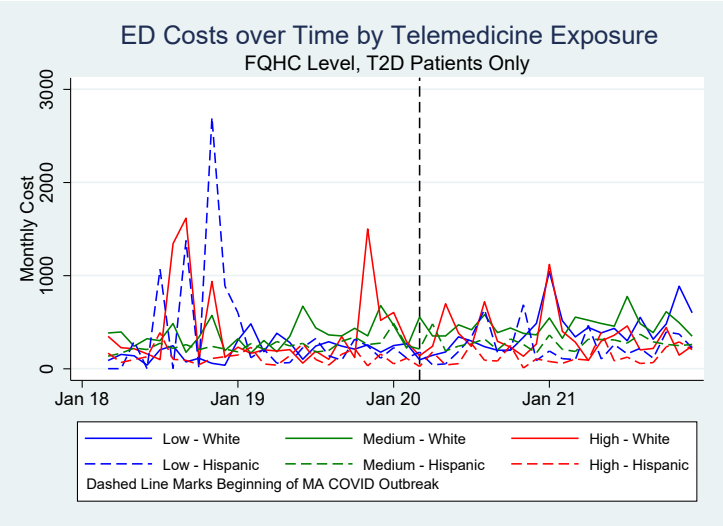


Figure A3h: Inpatient Costs

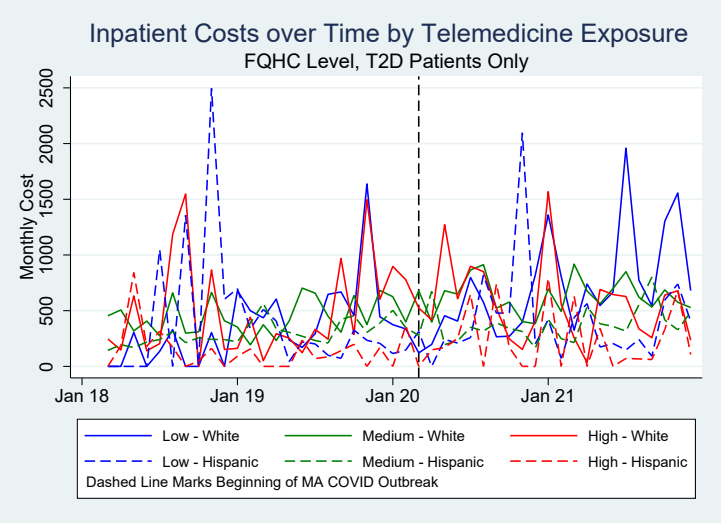


Figure A3i: Total Costs

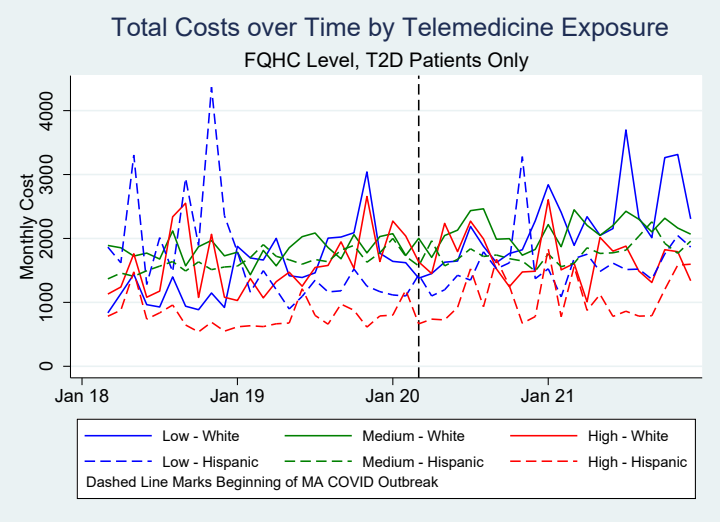


Figure A3j: Systolic Blood Pressure

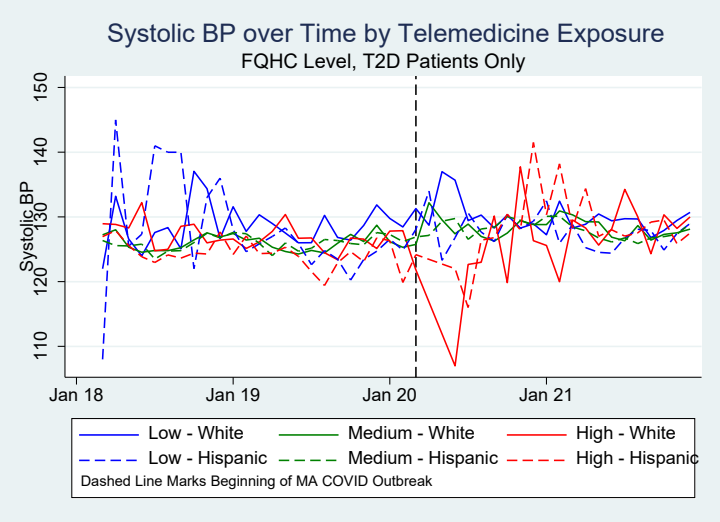


Figure A3k: Diastolic Blood Pressure

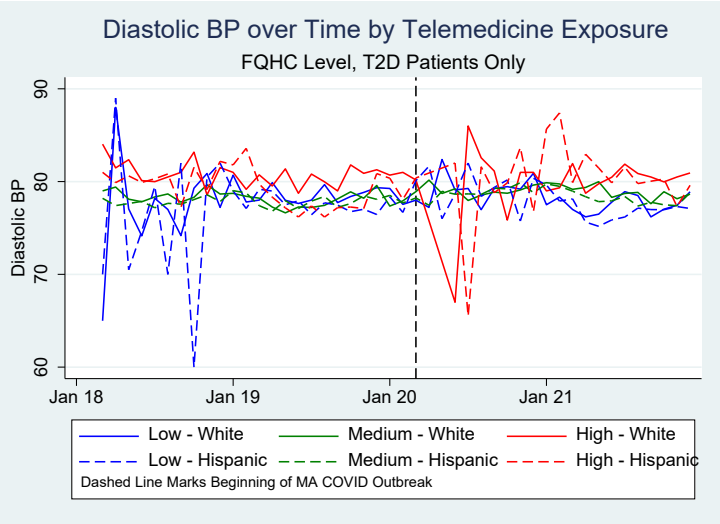


Figure A3l: Blood Glucose

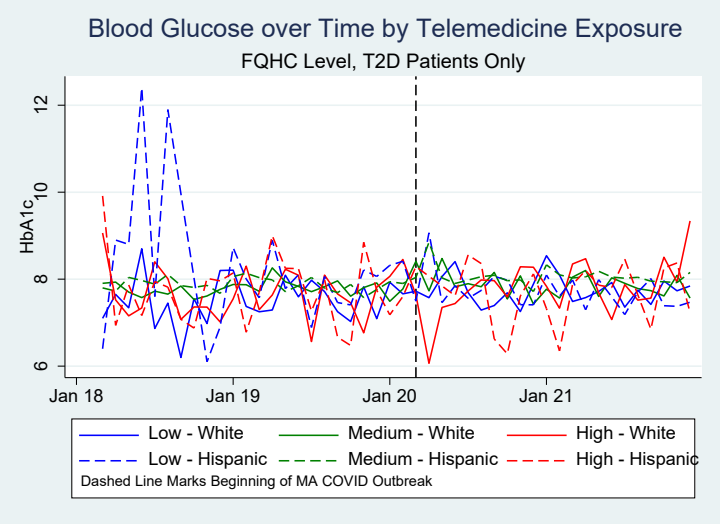


Figure A3m: Retina Exam

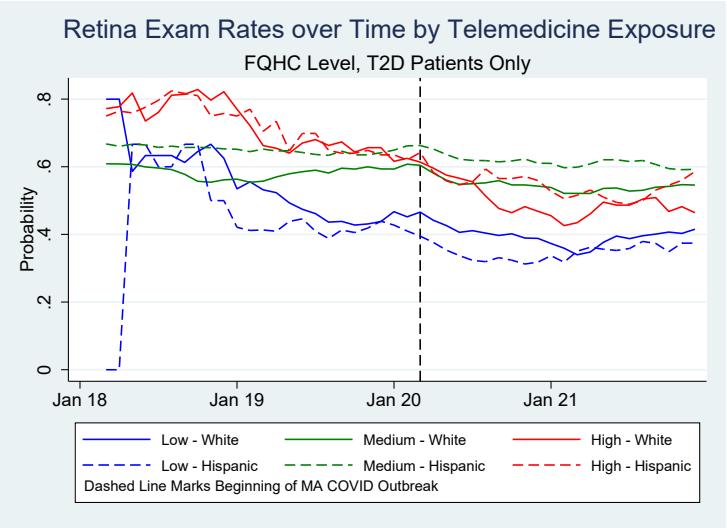


Figure A3n: Blood Pressure Control

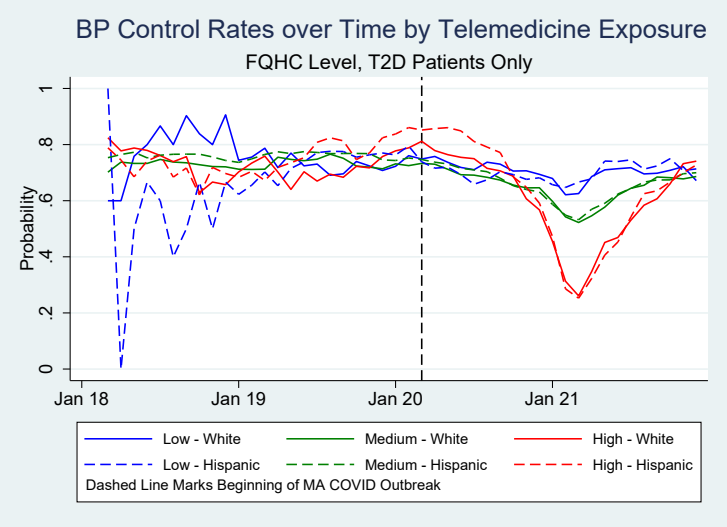


Figure A3o: Poor Blood Glucose Control

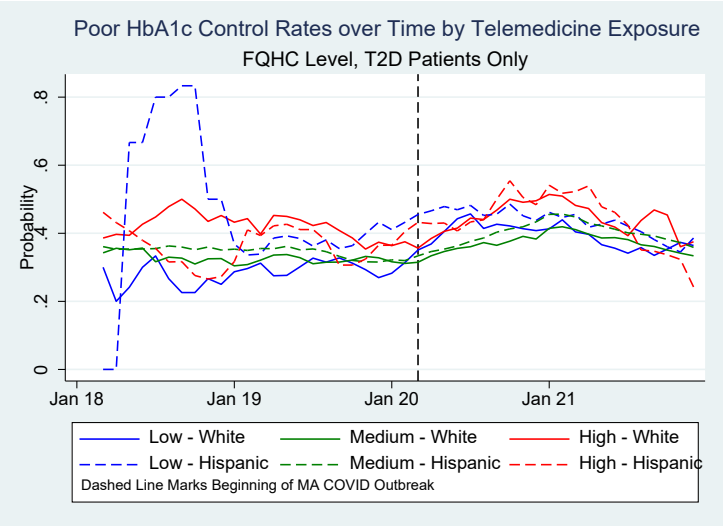


Table 3.A1: C3 Cohort Demographics

Demographic	**Observations (n=216,125)**	**Beneficiaries (n=5,509)**
FQHC-level Telehealth Exposure		
Low	18012 (8.3)	532 (9.7)
Medium	185897 (86)	4669 (84.8)
High	12216 (5.7)	308 (5.6)
Mean Age (SD)	50.4 (10.2)	48.9 (10.5)
Sex, N (%)		
Female	128914 (59.7)	3275 (59.5)
Male	87211 (40.4)	2234 (40.6)
Race, N (%)		
White, NH	61560 (28.5%)	1563 (28.4)
Black, NH	39715 (18.4)	1027 (18.6)
Hispanic, any race	114850 (53.1)	2919 (53)
Primary Language, N (%)		
English	84957 (41.1)	2135 (40.4)
Spanish	76271 (36.9)	1907 (36.1)

Other Language	46 (0.02)	1 (0.02)
Unknown	45566 (22)	1241 (23.5)
Top 5 Zipcodes, N (%)		
01040	16355 (7.5)	378 (6.9)
01902	14926 (6.9)	376 (6.8)
02301	13195 (6.1)	347 (6.3)
02128	8085 (3.7)	206 (3.7)
01610	7975 (3.7)	197 (3.6)
Condition, N (%)		
Mental Health History	164115 (75.9)	4126 (74.9)
Substance Use History	88670 (41)	2220 (40.3)
Asthma	68416 (31.7)	1684 (30.6)
COPD	43047 (19.9)	1052 (19.1)
Cardiovascular Disease	54171 (25.1)	1357 (24.6)
Ischemic Heart Disease	37807 (17.5)	950 (17.2)
Myocardial Infarction	9368 (4.3)	233 (4.2)
Atrial Fibrillation	8188 (3.8)	208 (3.8)
Cerebral Vascular Incident	14972 (6.9)	372 (6.8)
Heart Failure	16924 (7.8)	421 (7.6)
Hypertension	162485 (75.2)	4107 (74.6)
Hyperlipidemia	99107 (45.9)	2512 (45.6)

Table 3.A2: CurrentCare Demographics

	Patient-Months	**People**
Portal Use Levels (%)	*N=2,040,947*	*N= 84,240*

No use (0 Views)	1692197 (82.9)	69449 (82.4)
Some use (1-14 Views)	204382 (10.0)	8812 (10.5)
High Use (15+ Views)	144368 (7.1)	5979 (7.1)
Mean Portal Visits (SD)	6.99 (57.7)	5.84 (43.4)
Mean Age (SD)	58.3 (16.4)	55.1 (17)
Female (%)	1329522 (65.1)	49771 (59.1)
Race (%)		
White	1779722 (87.2)	73034 (86.7)
Black	142273 (7)	5951 (7.1)
Hispanic	118952 (5.8)	5255 (6.2)
3-Digit Zip: 029 (%)	653274 (32)	26967 (32)
Unhoused	25453 (1.3)	789 (0.9)
Diabetes	412966 (20.2)	11979 (14.2)
Hypertension	1112675 (54.5)	36746 (43.6)
Hyperlipidemia	938643 (46)	30296 (36)
DHH	293899 (14.4)	7915 (9.4)
Angina	219243 (10.7)	5857 (7)
Heart Failure	188637 (9.2)	4955 (5.9)
Peripheral Artery Disease	17958 (0.9)	447 (0.53)
AIDS	7862 (0.4)	237 (0.3)
Connective Tissue Disease	4187 (0.2)	99 (0.1)
Rheumatoid Arthritis	48058 (2.4)	1205 (1.4)
Dementia/Alzheimers	54761 (2.7)	1699 (2)
Multiple Sclerosis	19063 (0.9)	526 (0.6)
Parkinson's	2496 (0.12)	65 (0.08)
Stroke	57690 (2.8)	1594 (1.9)

Cancer	177304 (8.7)	5085 (6)
Glaucoma	47217 (2.3)	1350 (1.6)
Depression	345278 (16.9)	10490 (12.5)
Alcohol Abuse	76765 (3.8)	2511 (3)
Asthma	380381 (18.6)	11743 (13.9)
COPD	94506 (4.6)	2622 (3.1)
Chronic Kidney Disease	195060 (9.6)	5133 (6.1)

Figures 3.A4a-3.A4i: Un-adjusted Outcome Trends (Black – White)

Figure A4a: Total Encounters

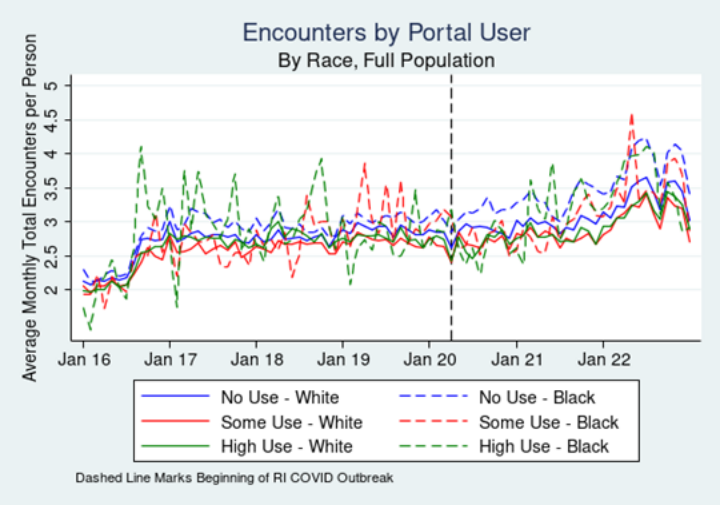


Figure A4b: ED Encounters

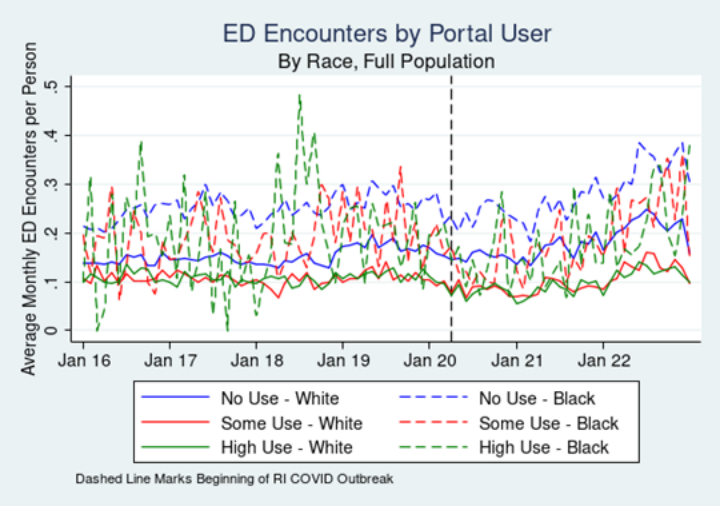


Figure A4c: Inpatient Encounters

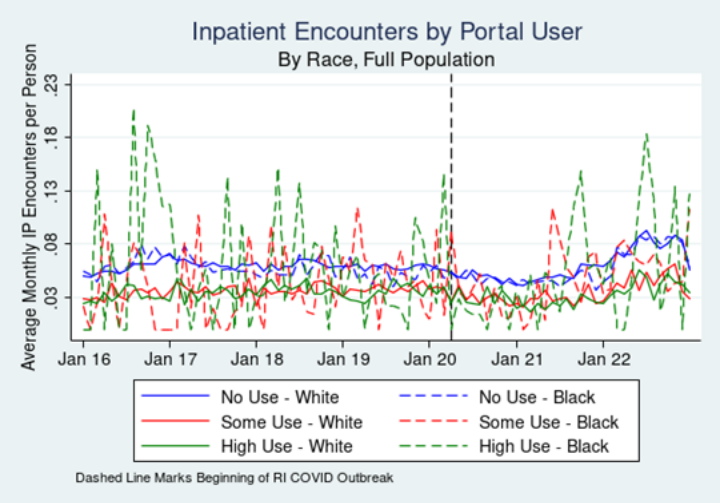


Figure A4d: Outpatient Encounters

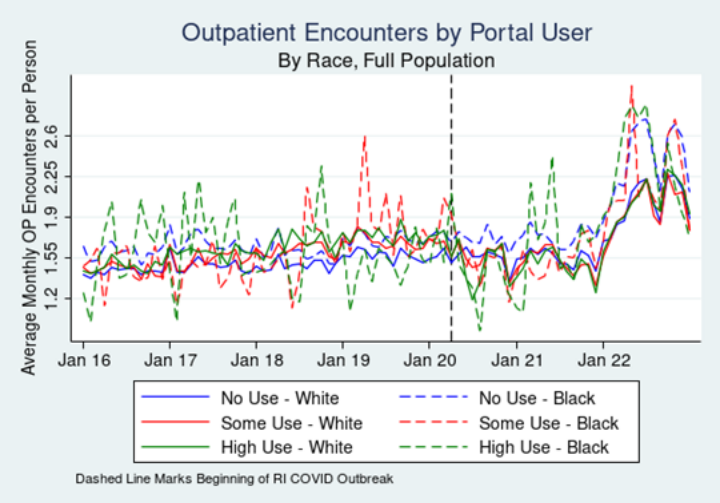


Figure A4e: Lab Encounters

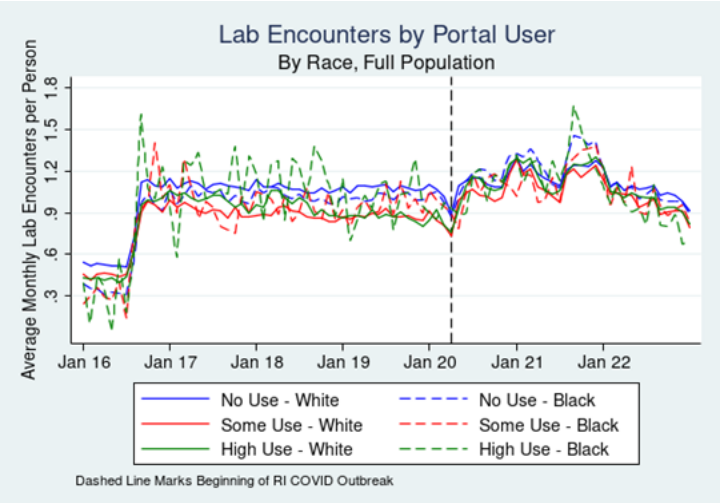


Figure A4f: Blood Glucose

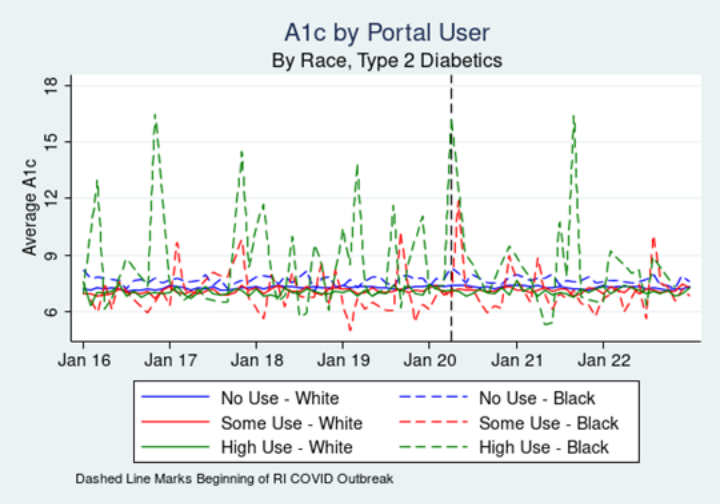


Figure A4g: Systolic Blood Pressure

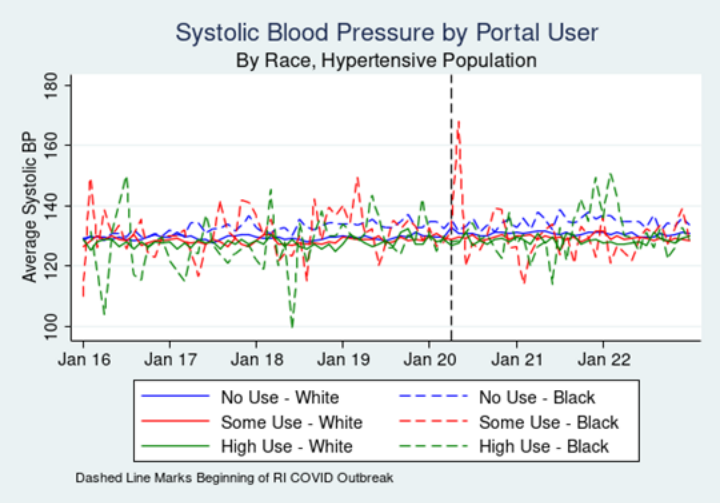


Figure A4h: Diastolic Blood Pressure

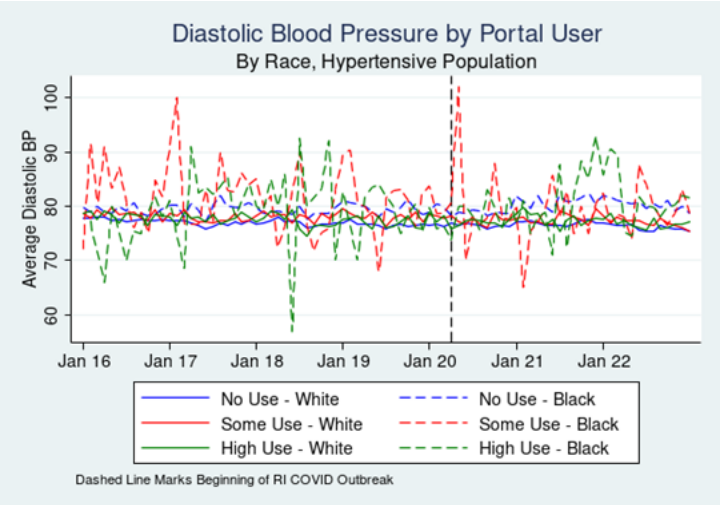
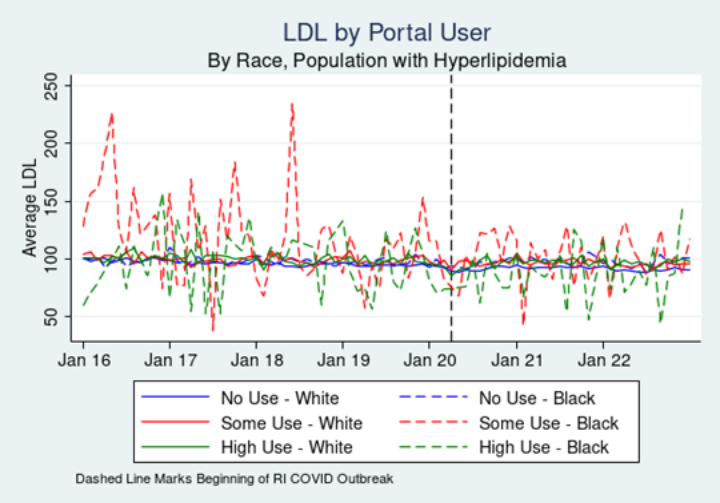


Figure A4i: LDL



Figures 3.A5a-3.A5i: Un-adjusted Outcome Trends (Black – White)

Figure A5a: Total Encounters

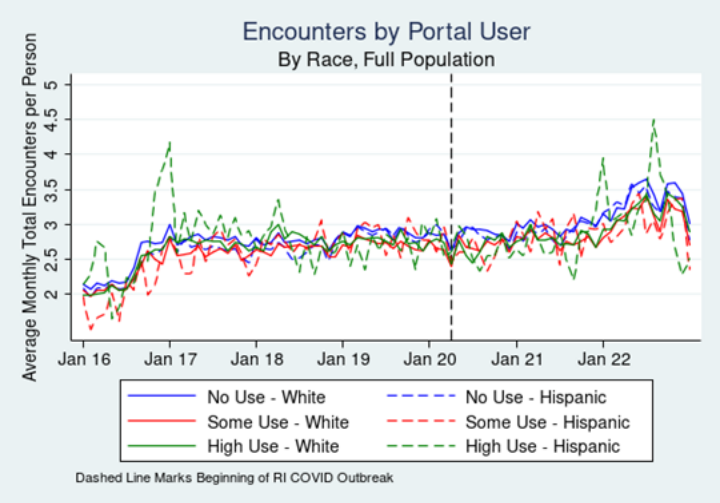


Figure A5b: ED Encounters

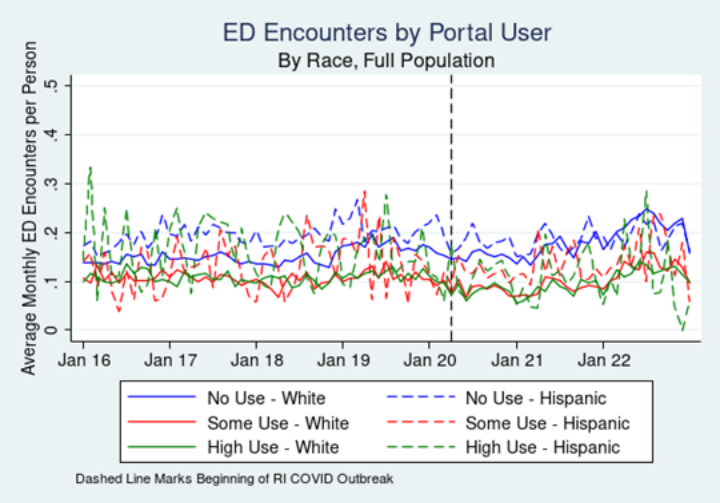


Figure A5c: Inpatient Encounters

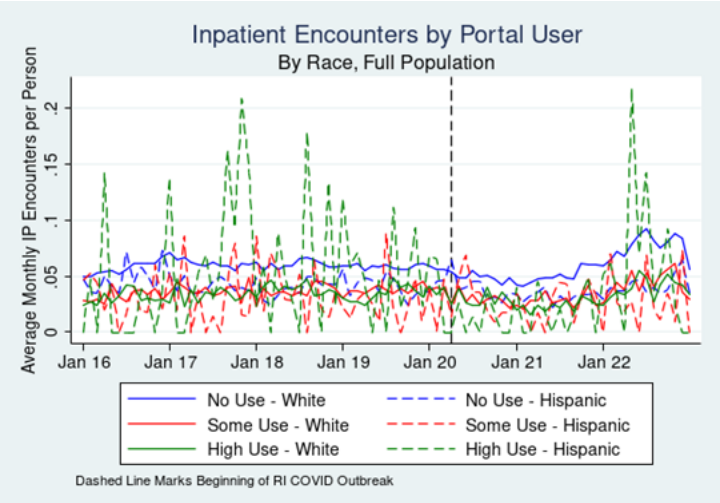


Figure A5d: Outpatient Encounters

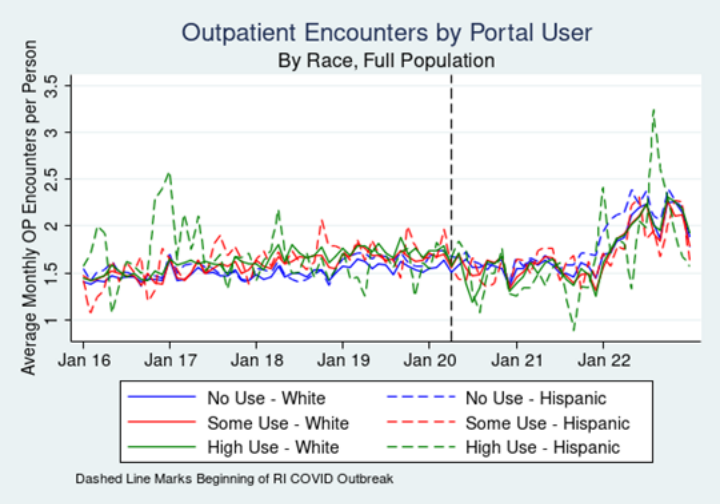


Figure A5e: Lab Encounters

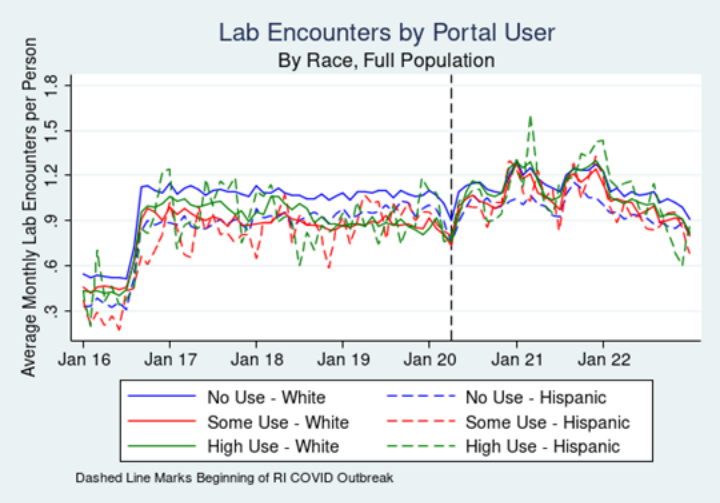


Figure A5f: Blood Glucose

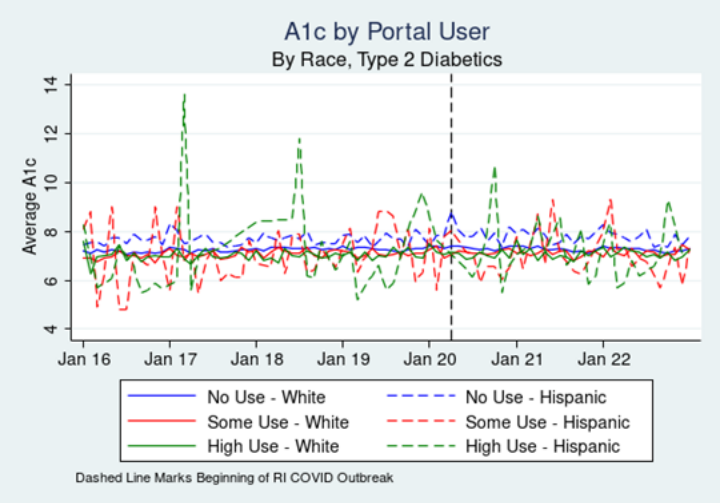


Figure A5g: Systolic BP

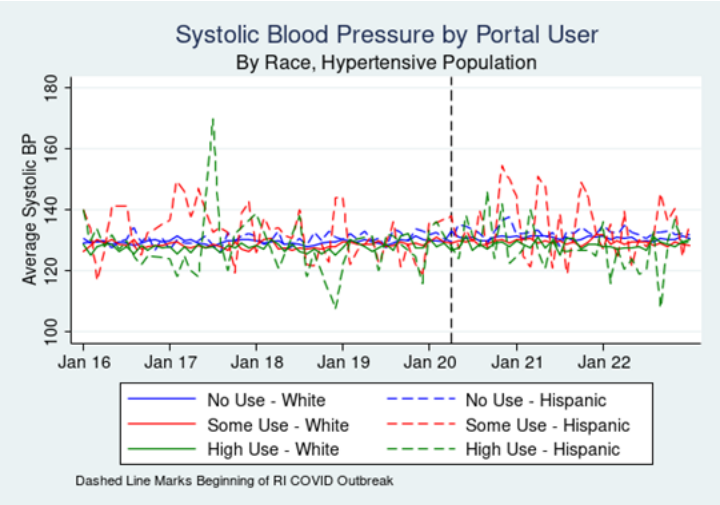


Figure A5h: Diastolic BP

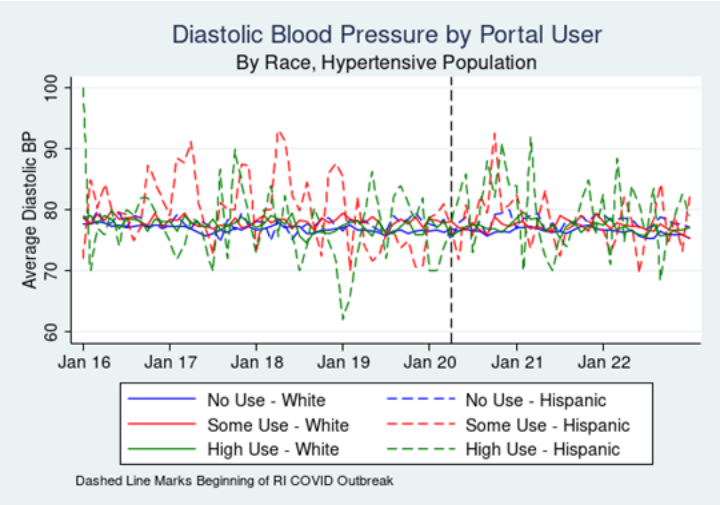
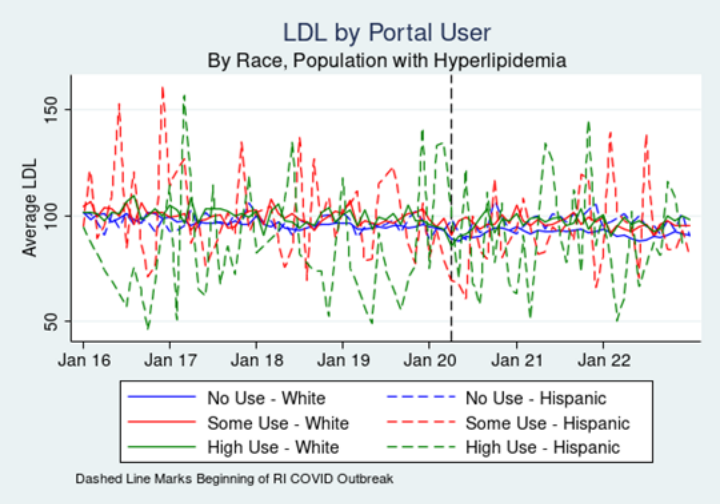


Figure A5g: LDL



[Figure 3.A6a-3.A6r](): Lagged Pre-Trends Estimates

Figure A6a: Encounters (Black – White)

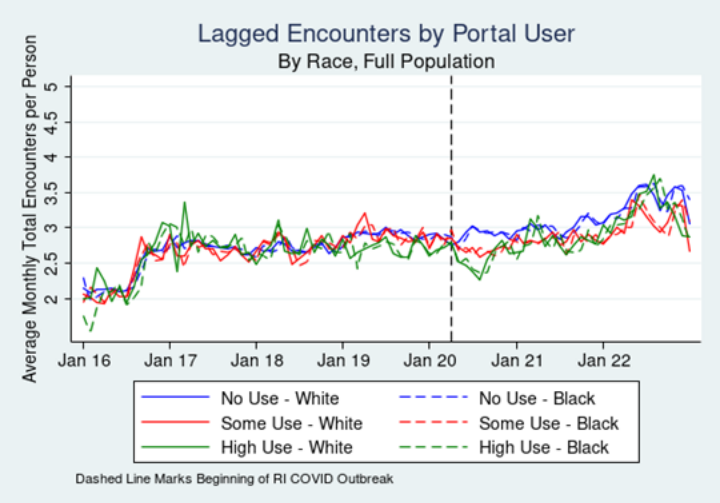


Figure A6b: Encounters (Hispanic – White)

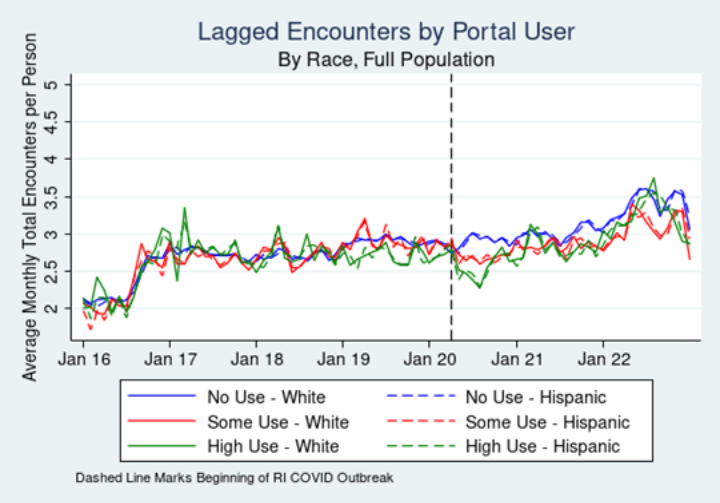


Figure A6c: ED Encounters (Black – White)

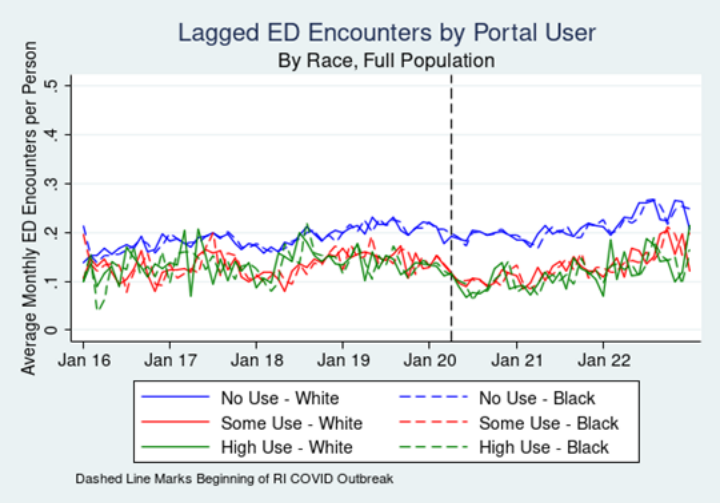


Figure A6d: ED Encounters (Hispanic – White)

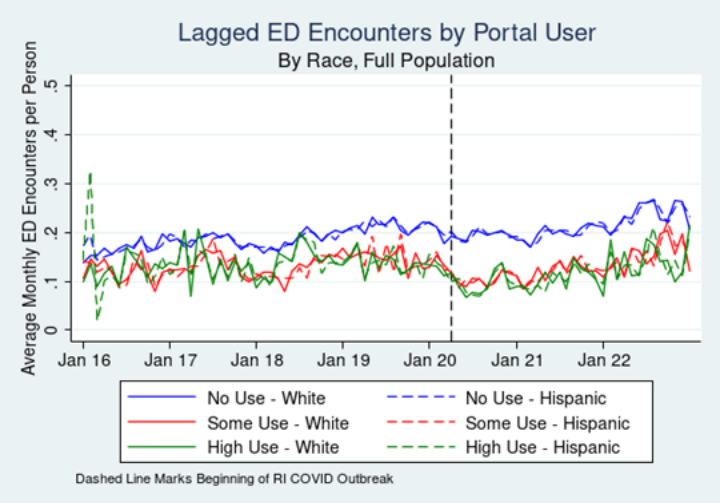


Figure A6e: Inpatient Encounters (Black – White)

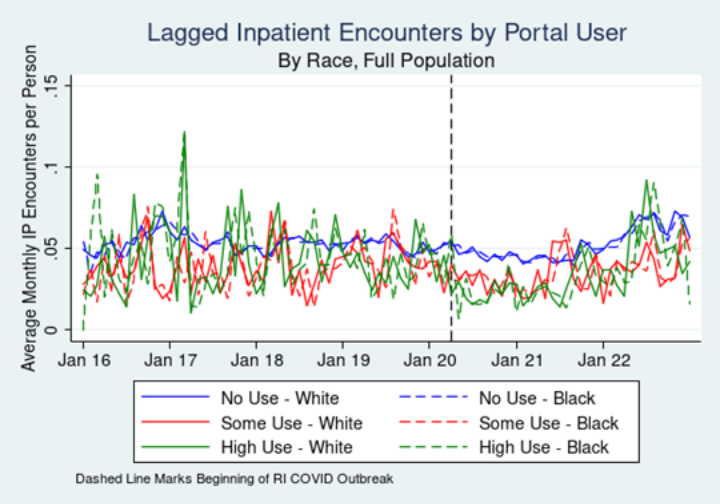


Figure A6f: Inpatient Encounters (Hispanic – White)

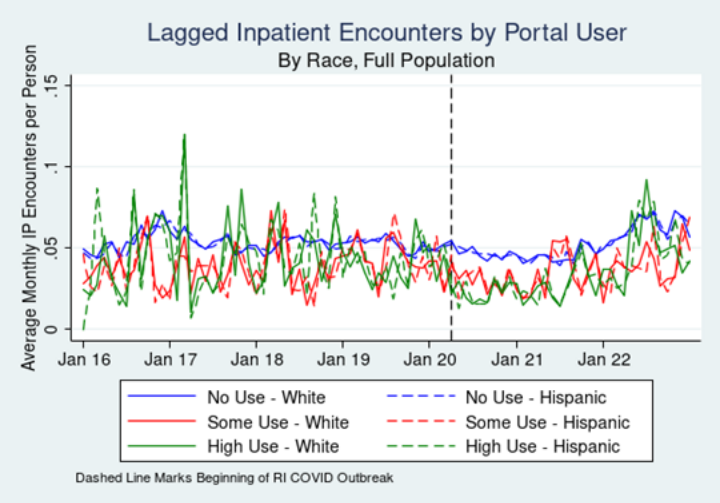


Figure A6g: Outpatient Encounters (Black – White)

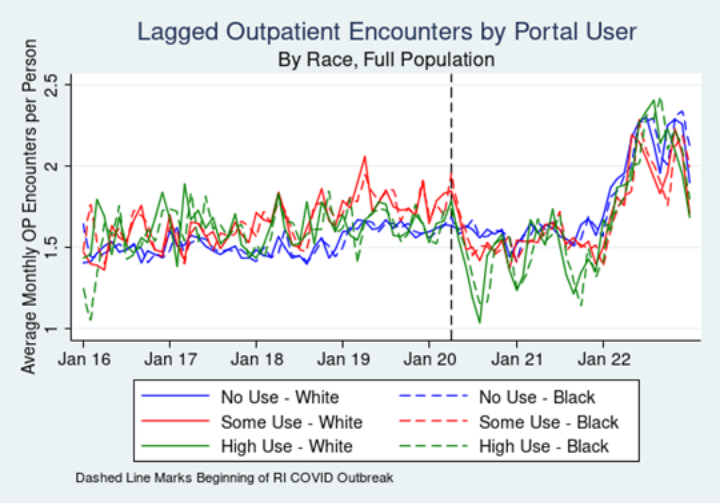


Figure A6h: Outpatient Encounters (Hispanic – White)

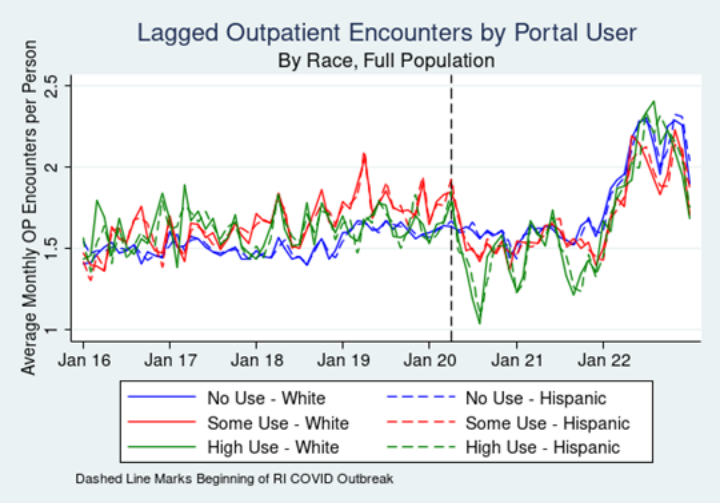


Figure A6i: Lab Encounters (Black – White)

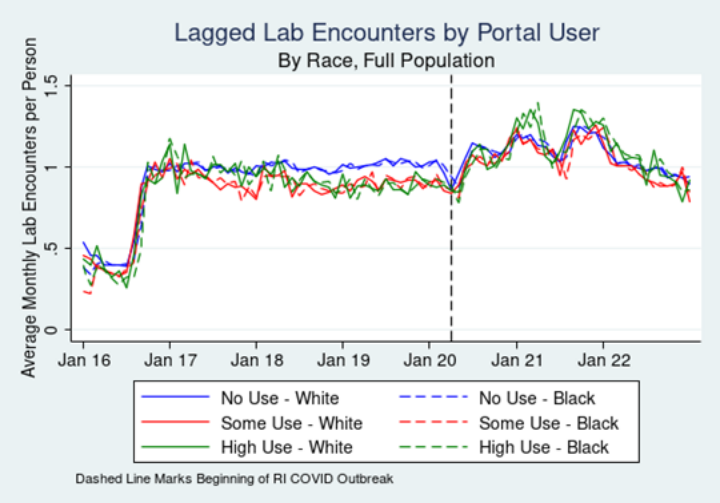


Figure A6j: Lab Encounters (Hispanic – White)

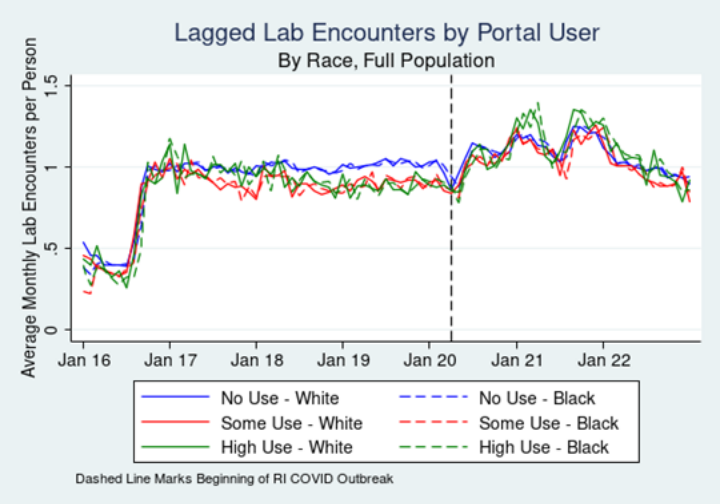


Figure A6k: Blood Glucose (Black – White)

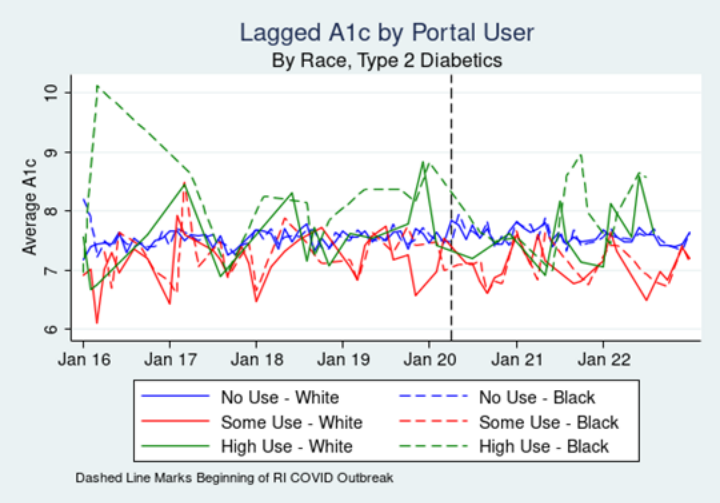


Figure A6m: Blood Glucose (Hispanic – White)

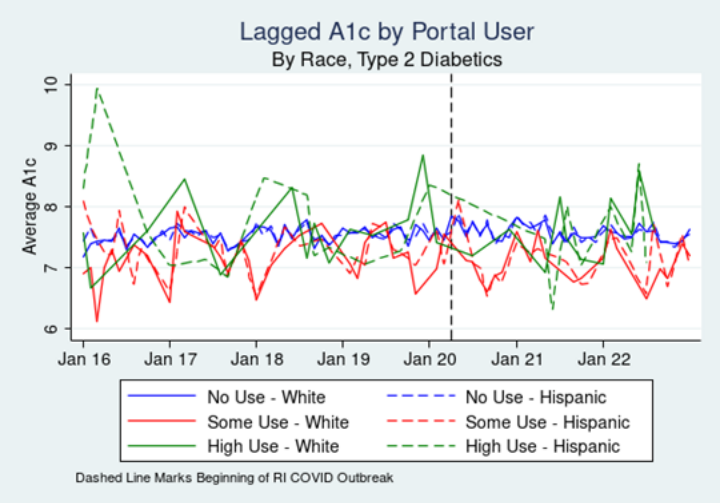


Figure A6m: Systolic BP (Black – White)

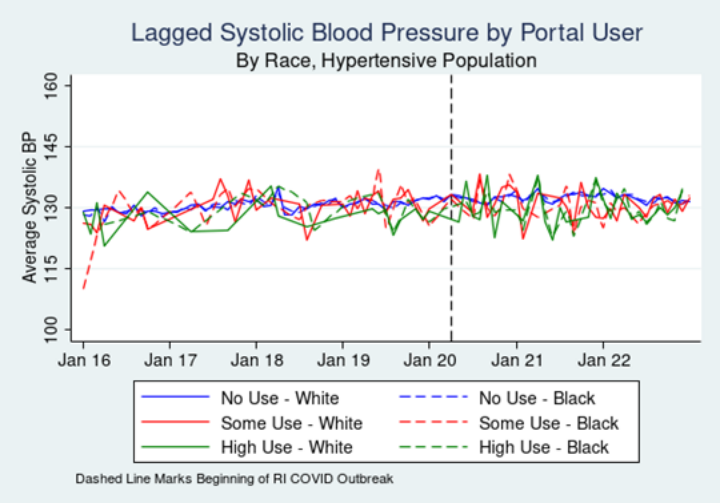


Figure A6n: Systolic BP (Hispanic – White)

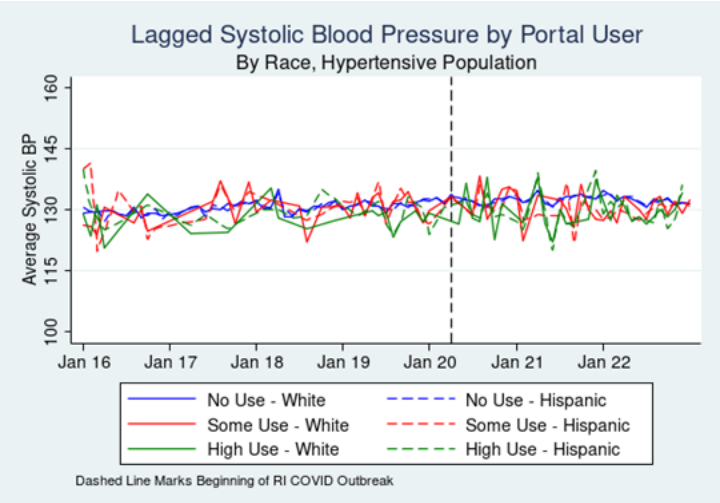


Figure A6o: Diastolic BP (Black – White)

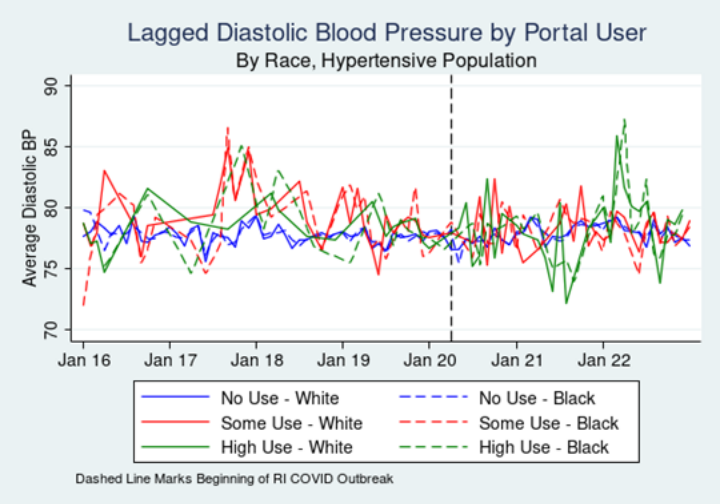


Figure A6p: Diastolic BP (Hispanic – White)

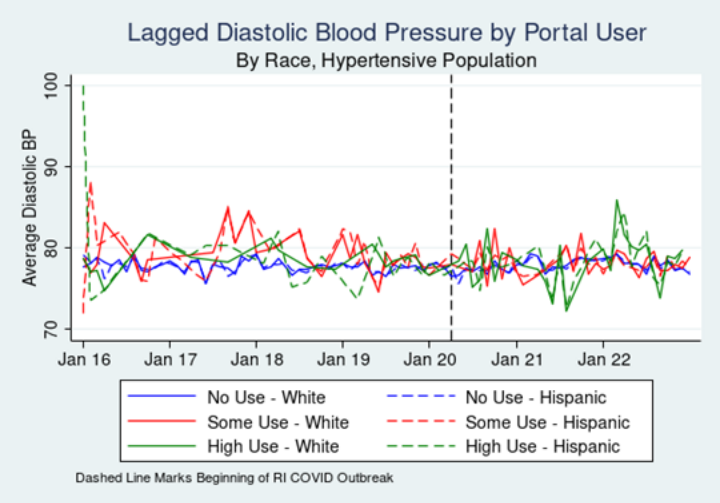


Figure A6q: LDL (Black – White)

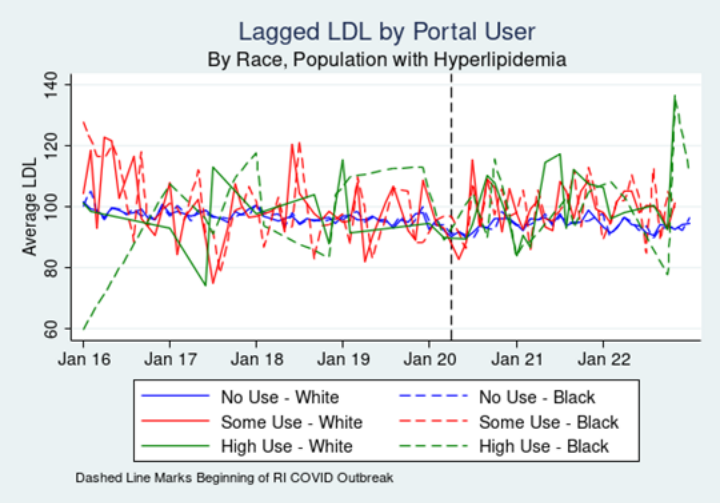
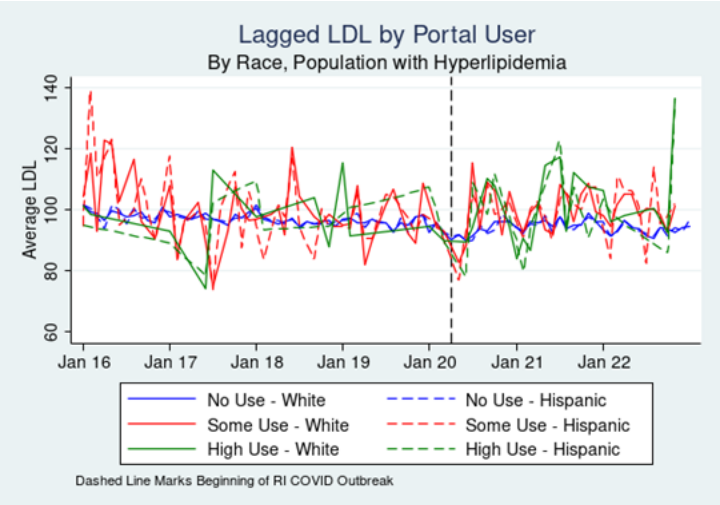


Figure A6r: LDL (Hispanic – White)



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