Does Telemedicine Transcend Disparities or Create a Digital Divide? Evidence from the COVID-19 Pandemic

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Abstract

We examine telemedicine utilization during the COVID-19 pandemic. Advocates have argued that telemedicine can overcome barriers in accessing healthcare and protect patients from contracting COVID-19. Rural and poor patients, for example, would not need to make expensive and time-consuming trips to healthcare facilities when using telemedicine. Conversely, telemedicine adoption may depend on broadband access and technology skills, which could create a digital divide and exacerbate disparities. We study these questions using data on virtual and conventional care from a large commercial insurer. Telemedicine utilization soared during the pandemic. We further find that telemedicine utilization was concentrated in urban and affluent markets. We attribute this to two factors. First, telemedicine use was correlated with broadband penetration. Second, telemedicine adoption was much higher for patients with an established healthcare provider relationship (i.e., received care in the same health system in the previous year). We also find that telemedicine utilization was lower among older patients and comorbidities; cohorts with the greatest risk of severe illness and death from COVID-19. Without further intervention, telemedicine could exacerbate existing health care disparities.

Keywords: *Healthcare Disparities, Telemedicine, COVID-19 pandemic, Digital Divide, Healthcare IT*

1. INTRODUCTION

The COVID-19 pandemic has resulted in 568,000 deaths in the US and 3 million worldwide[1]. To slow the spread of the coronavirus, authorities have advocated that communities practice social distancing. Healthcare providers have responded by providing virtual care, known as telemedicine. This has allowed providers to deliver care while avoiding in-person consultations. Although telemedicine accounted for less than 1% of outpatient care before the pandemic, nearly a half was delivered via telemedicine during the initial stages of the pandemic.[2]

Telemedicine has traditionally been seen as an intervention to overcome barriers to the delivery of healthcare (Hwang et al. 2017, Mehrotra et al. 2016). Rural patients can use telemedicine to connect digitally with healthcare providers (who are often located in urban centers) and thus avoid making long and expensive trips to receive care.[3] Patients with impaired mobility can connect digitally with healthcare providers without leaving their homes and thus avoid difficult in-person trips to healthcare facilities (Mehrotra et al. 2016). Telemedicine could allow low-income patients to access healthcare without taking time off work to travel to and wait for service at healthcare facilities (George et al. 2012). Minority and low-income patients have a higher disease burden and face barriers to accessing care (Warner and Brown 2011). With telemedicine use likely to persist even after the end of the pandemic (RAND Review 2020), this technology could play an important role in overcoming both access barriers and health care disparities.

Telemedicine could, alternatively, create new access barriers and exacerbate existing healthcare disparities. This may occur through two mechanisms. First, established users may receive priority for

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[1] Numbers obtained from Google.com's dashboard on 21st April 2021.
[2] Author's calculations for the state of Michigan.
[3] For example, Seema Verma, the former administrator of the Centers for Medicare and Medicaid Services stated in November 2020 "We expanded telehealth because of its potential for rural areas where transportation over long distances can be difficult and providers are often in short supply." (Verma 2020) This indicates how the upper echelons of health policy leadership view telemedicine as a tool to reduce disparities and increase healthcare access.

digital services (Guerrero et al. 2007). Affluent and urban populations utilize more conventional healthcare services (Dickman et al. 2017) and this pattern could easily continue in a virtual care environment. Second, poor broadband access and limited familiarity with information technology may create a barrier to accessing virtual healthcare (Agarwal et al. 2009, Roberts and Mehrotra 2020). Telemedicine may thus create a 'digital divide' for healthcare services.

Telemedicine allows healthcare to be provided in a socially distanced manner. Its ability to reduce coronavirus transmission while simultaneously providing healthcare has been suggested by the Centers for Disease Control and the US Department of Veterans Affairs (CDC 2020, VAntage Point 2020). Telemedicine could thus be targeted towards patients most likely to become severely ill if they contract COVID-19. This is especially relevant for patients in communities with high COVID prevalence, older patients, and those with relevant comorbidities (CDC 2021).

Policymakers and healthcare providers have recognized the need for research on telemedicine utilization during the pandemic and its impact on healthcare disparities (Bakhtiar et al. 2020, Ortega et al. 2020, Roberts and Mehrotra 2020). We address this question by using a novel data set that tracks outpatient care for commercially insured Michigan patients. These data comprise the universe of the insurer's claims, with detailed socio-demographic information on beneficiaries and health care providers. These data also document virtual and conventional care utilization.

Our analysis generates three significant findings. First, telemedicine utilization grew from less than 1% of outpatient claims before the pandemic to half of the care provided during the pandemic. Second, utilization of telemedicine seemed to exacerbate healthcare disparities with higher utilization among urban patients in affluent communities with greater broadband penetration. We further find that patients with established care relationships utilized virtual care at a much higher rate. Third, telemedicine utilization was higher among patients with lower health risks from contracting COVID-19. Older patients and those with comorbidities, such as diabetes, immune system deficiency, and renal failure were less likely to receive care via telemedicine. Although these groups are more likely to develop complications on contracting the coronavirus, patients with these conditions received healthcare via conventional in-person visits during the pandemic.

Our findings have implications for policymakers and healthcare administrators. The switch to telemedicine presents a unique opportunity for reducing healthcare access barriers, but only if policymakers address the digital divide. Policy should be framed to promote broadband access and technology adoption to increase telemedicine utilization in rural areas so that existing healthcare disparities are not exacerbated in a digital environment. Policy should also be framed to encourage telemedicine utilization for patients most likely to get severely ill from COVID-19. The shift to telemedicine presents a unique opportunity for hospital administrators to expand the communities they serve. Hospitals could enroll patients in more distant communities, especially those in rural areas that have traditionally been underserved. This represents an untapped client base for hospitals and may simultaneously bring services to underserved communities.

2. TELEMEDICINE

Although telemedicine was seldom used before the pandemic, a wide body of research examined the impact it could have on healthcare (Mehrotra et al. 2016). One stream of research argued that there are multiple benefits to providing care digitally; such as reducing disparities in care utilization, increasing provider productivity, and improved patient satisfaction (e.g., Ayabakan et al. 2020, Hwang et al. 2017, Rajan et al. 2019, Sun et al. 2020). Other studies have argued that telemedicine has limited or even detrimental effects, such as increased follow-up care (e.g. Bavafa et al. 2018).

Before the pandemic, fewer than 1% of outpatient visits were provided via telemedicine (Mehrotra et al. 2016). There are multiple reasons for historically low telemedicine utilization. Providers may have preferred in-person care where they could conduct physical examinations (Hjelm 2005). Many insurers restricted coverage and reimbursement for telemedicine before the pandemic due to concerns that it could increase the quantity of low-value care (Medicare Payment Advisory Commission 2021). Patients may have been unfamiliar with virtual care technologies and reluctant to utilize telemedicine (Lin et al. 2020, Paul et al. 1999). Social distancing regulations during the pandemic have increased telemedicine utilization, mirroring shifts to digital services in other sectors of the economy (Brynjolfsson et al. 2020).

Telemedicine may theoretically expand access to healthcare. Service providers and users do not need to be co-located due to the negligible transportation cost for digital services (Goldfarb and Tucker 2019).[4] When providing healthcare via telemedicine, patients can obtain medical advice via telephone or virtual connection with their providers. Patients in rural areas and those with impaired mobility have the highest transportation cost and could benefit the most from telemedicine.

Telemedicine may, conversely, create a digital divide and limit healthcare access for two reasons. First, firms often prioritize digital services for existing customers. This allows firms to demonstrate customer focus and to maintain continuity of service for existing customers (Guerrero et al. 2007, Prins and Verhoef 2007). As in-person healthcare is utilized disproportionately by the affluent population located in urban areas, the shift to telemedicine could potentially reinforce existing disparities in healthcare utilization (Smedley et al. 2003). Second, access to and knowledge of information and communication technologies may limit an individual's utilization of digital services. Individuals who do not have a telephone, computer, or broadband connection may not be able to access digital services (Hjort and Poulsen 2019). Lower-income users and those in rural areas may be unable to afford broadband which tends to be more expensive in rural areas. Further, an individual's

[4] Also referred to as the flat world hypothesis (e.g. Friedman 2006).

human capital and familiarity with technology would determine the ease with which they can shift to telemedicine (Aubert et al. 2006).

3. DATA AND METHODS

3.1 Data

We utilize data from the Blue Cross Blue Shield of Michigan. The sample comprises the universe of ambulatory and outpatient claims for 3.5 million beneficiaries in all Michigan counties from January 7th through June 14th of 2019 and 2020. Michigan provides an appropriate setting for the examination of our research question due to the early and intense spread of the coronavirus as well as its diverse population and significant rural-urban variation. These data describe whether a visit was conventional or virtual, as well as the health care providers' identities, locations, and tax identification numbers (TIN). The data also capture patients' demographics (age and sex) and locations (home zip codes).

We combine these medical claims data with three additional sources to test whether telemedicine expands access or creates a digital divide. The 2018 and 2020 American Community Survey (ACS) provides the African American population share and broadband penetration rate for each zip code respectively.[5] IRS Statistics of Income (SOI) data provides the 2017 average income and the US Department of Agriculture measures rurality for each zip code. We define Rural as an indicator equal to 1 for Rural-Urban Commuting Area Codes 5-7 and 9-12 and zero otherwise.

Health care systems are defined using a combination of billing identifiers and the Torch Insight data. The administrative claims include both individual provider identifiers, National Provider Identification (NPI) numbers, and TINs. Providers that share a common TIN for the majority of

[5] Demographic measures of race, income and broadband are used as these variables are not captured in our administrative claims data.

visits are defined as members of the same system. Torch Insight data tracks provider organizations for analytics and marketing, identify systems that comprise multiple TINs. A patient and health system have an established relationship if a patient had at least one encounter with a given health system in the preceding year.[6] These measures are based on the entire 2018 and 2019 claims data sets, not just our January through June analytic samples.

Telemedicine utilization may depend on patients' health risks. We examine five sets of chronic conditions that place patients at an elevated risk from the COVID-19 pandemic: cancer, chronic obstructive pulmonary disease (COPD), diabetes, renal failure, and immune deficiency. The health risks of COVID-19 (i.e., hospitalization and death) are significantly higher for older patients and patients with these chronic conditions (CDC 2021). Finally, Michigan's Coronavirus Daily Cases data track variation in public health risk across time and counties. Our analyses use daily confirmed cases.[7]

Figure 1 depicts the aggregate daily care volumes in 2019 and 2020. The volume of ambulatory visits exhibit strong day-of-week seasonality. The day-of-week by calendar date relationships differ from 2019 to 2020 and leap year further shifts this relationship within our study period. The 'polar vortex,' a winter storm from January 28–February 1 of 2019, drastically reduced ambulatory visit volumes (Burns, 2019). We control for this polar vortex in our empirical specification. To estimate our base models, we count the number of telemedicine and conventional claims by zip code (denoted by $\boldsymbol{m}$) and date $(\boldsymbol{t})$. We employ a seven-day moving average smoother to address day-of-week seasonality.

[6] Lagged relationships are used as contemporaneous relationships may be a function of either the COVID-19 pandemic or telemedicine utilization.

[7] The data also track probable cases. The incremental number of probable cases is small and highly correlated with confirmed cases. Results are robust to including confirmed and probable cases.

3.2 Model and Estimation

To estimate the effect of the pandemic on conventional and telemedicine utilization, we employ a difference-in-differences strategy. We difference smoothed telemedicine utilization between 2020 and 2019 ($\Delta Telemed_{mt}$). We normalize this change to the smoothed 2019 total visit volume and define our dependent variable as the telemedicine conversion rate, $\frac{\Delta Telemed_{mt}}{Visits_{mt-365}}$. By normalizing our dependent variable to 2019 visit volumes, the regression coefficient can simply be interpreted as the 'proportion of counterfactual care that was provided via telemedicine.'

We regress the telemedicine conversion rate for market $\boldsymbol{m}$ at time $\boldsymbol{t}$ on a $Post\ COVID$ indicator:

$$\frac{\Delta Telemed_{mt}}{Visits_{m,t-365}} = \alpha + \beta Post\ COVID_t + \gamma \mathrm{Vortex}_{\mathrm{t-365}} + \mu_m + \epsilon_{mt}, \qquad (1)$$

where the fixed effects (μ_m) capture time-invariant differences across markets and ϵ_{mt} is an error term. The parameter α measures the year-on-year growth in telemedicine volume before the pandemic. The parameter β captures the percent of counterfactual visits that were converted to telemedicine during the pandemic. All specifications control for the 2019 polar vortex, which is captured by the parameter γ. As our dependent variables and ***Post COVID*** are differenced over time, we omit time fixed-effects. Our model is estimated by ordinary least squares with robust standard errors clustered by market. Observations are weighted by 2019 visit volumes $(Visits_{m,t-365})$ as there is a correlation between market sizes and telemedicine adoption.[8]

In subsequent specifications, we allow the telemedicine response to be heterogeneous across market characteristics. We achieve this by interacting the ***Post COVID*** indicator with the proportion of the population that is African-American, average income, and percent with broadband

[8] Unweighted results are qualitatively similar.

in the market respectively. We also include the number of COVID cases in our empirical specification. These variables are demeaned before including them in the regression. We omit observations during the initial days of the pandemic (March 4th to 24th) for two reasons. First, our empirical approach applies a seven-day smoother to the dependent variable. Omitting the interim period from our estimation prevents the smoother from spreading post-COVID telemedicine into the pre-COVID period, which would bias our parameters towards zero. Second, Michigan's response to the coronavirus was not immediate; although COVID entered the state by early March, the first case was not confirmed until March 10th and the state's policy response was gradually increased through March 23rd. Providers' telemedicine responses also appear to have lagged state policy (and the pandemic) by two to three weeks. The findings, however, are robust to changes in interim period dates.

We employ several alternative specifications to allow for parameter heterogeneity. We allow β to vary across patient or provider subgroups. In these cases, data are aggregated at a more granular level (e.g., established care relationships, age, or comorbidities associated with a heightened risk of death from COVID-19) and the subgroup variable is interacted with the post-COVID indicator. These specifications also include fixed effects for the more granular subgroups.

The pandemic also affected conventional care. We define the dependent variable as the change in conventional care from 2020 to 2019 normalized to the 2019 total visit volumes, $\frac{\Delta Con.Care_{mt}}{Visits_{m,t-365}}$. These specifications are otherwise identical to our telemedicine models.

3.3 Threats to Identification and Robustness Tests

We discuss threats to our identification before presenting our results. Our empirical approach relies on a difference-in-differences identification strategy. We utilize 2019 data as a comparison group for our 2020 data. Unobserved differences between these two groups are assumed to be time-invariant. Figure 1 indicates that, except for day-of-week seasonality and the polar vortex, 2019 visit volumes are highly correlated with 2020 visit volumes. This similarity in pre-COVID volumes holds if we examine conventional visits, virtual visits, or total visits. We formally test for differences in the pre-COVID (i.e., January – March 5) conversion rates using a relative time model (Angrist and Pischke 2008). Consistent with the graphical results, we cannot reject the assumption that pre-COVID differences between the 2019 and 2020 samples are time-invariant. A detailed description of the test and results are presented in the appendix (page A1 and Table A1 in the supplementary appendix). Finally, we demonstrate that our results are robust to utilizing a market-specific time trends model (Angrist and Pischke 2008). These results are reported in Table A2 of the Supplementary Appendix.

4. RESULTS

Figure 2 presents trends in smoothed conventional and total visit volumes in 2020. Pre-pandemic volumes followed a relatively stable trend, with about 33,500 visits per day. Nearly all pre-pandemic visits (99.8%) were conventional. Visit volumes plummeted in March, with conventional visits quickly falling to about 30 percentage points of the pre-pandemic levels. Telemedicine visit volumes (the difference between conventional and total visits) rose quickly following the pandemic, converting about 30 percentage points of pre-pandemic volumes to telemedicine or about half the post-pandemic care volume. These findings are empirically verified in Tables 2 and 3. These effect remains stable as we condition on geographic variation in rurality (Model 2), average income (Model 3), and the percent African American (Model 4). These patterns continue as we condition on broadband access and local COVID incidence (Model 5).

Tables 2 and 3 provide further insight into whether and how virtual and conventional care changed following the pandemic. Model 2 results demonstrate that about 21 percentage points of rural care are converted to telemedicine, 8 percentage points less than in non-rural markets. About half of this shortfall, 4.6 percentage points, is supplied through additional conventional care utilization. Telemedicine utilization is also more prevalent among patients in affluent communities (Model 3), where the conventional care reduction is slightly larger. These income effects are modest, as a $20,000 increase in average income is associated with a 1 percentage point increase in telemedicine and a 0.6 percentage points decrease in conventional care. Conversion rates increase with the proportion of African Americans (Model 4), but these same communities continue to use more conventional care. However, the magnitudes and significance levels of the African American parameters are sensitive to specification. Finally, telemedicine utilization increases with broadband penetration, while conventional care utilization falls. The income and broadband results suggest that affluent patients are better able to substitute virtual care for conventional care.

We build on these findings by measuring telemedicine utilization for new versus established patients. We partition our data by health system, date, and patient-health system relationship. The data are analyzed at the health system level, with conversion rates calculated separately for the system's established patients, switching patients (those that had a relationship with other health systems), and new patients (with no health system relationship in the previous calendar year). We find that health systems disproportionately use telemedicine for their own established patient base. Results from Table 4, Model 1 demonstrate that a system's own patients have an 11 percentage point higher conversion rate. This does not appear to be driven by unobserved differences in patient health as patients switching from other systems utilize less telemedicine (although this coefficient is not statistically different than zero). These large differences in established patient utilization patterns are robust when controlling for patient age (Table 4, Models 3 and 4).

We also examine how telemedicine utilization responds to both public and patient health. Telemedicine utilization increases in the local incidence of COVID-19 cases (Table 2, Model 5), but the effect is vanishingly small. This small effect is robust to alternative specifications and measures of local COVID incidence.

The health consequences of COVID-19 vary widely across patients. The health consequences of COVID-19 are higher for older patients as well as those with cancer, COPD, diabetes, renal failure, and immune deficiencies (CDC 2021). This serves as a rationale for using telemedicine to provide socially distanced healthcare for these cohorts while maintaining social distancing. In nearly every case we find that higher-risk patients are significantly less likely to use telemedicine and more likely to use conventional care. Results in Table 4 indicate that telemedicine utilization decreases with patient age (Model 3) while conventional care utilization increases (Model 4). Table 5 results demonstrate that telemedicine utilization is approximately eight percentage points lower for patients with cancer, COPD, diabetes, and renal failure (Models 1-4). The immune deficiency difference is small and not significantly different from zero. Each of these groups is more likely to use conventional care (Table 6), but the differences are only significant for cancer, COPD, and diabetes.

Conventional and virtual care utilization begins to rise in mid-April (Figures 1 and 2). This was a period of rapid change and reorganization for health systems. It is plausible that telemedicine utilization and its differential uses for expanding access and or addresses public health risks could change over time. We examine this empirically by allowing our coefficients to vary over the duration of our panel. Results, presented in Appendix Table A4, suggest that the patterns described above are maintained throughout the period covered by our data.

5. DISCUSSION

Our findings indicate that telemedicine accounted for approximately one-third of pre-pandemic ambulatory care volumes and half of post-pandemic ambulatory care. Telemedicine utilization was higher among urban and affluent communities as well as for patients with established care relationships. Our findings suggest that telemedicine should not be expected to overcome existing health care disparities. Instead, telemedicine may exacerbate existing disparities and create a digital divide for health care services. Although telemedicine may slow the spread of COVID-19, patients with elevated COVID health risks, such as older patients and those with comorbidities were less likely to use telemedicine.

Our findings inform policy, practice, and research. Many health care commentators have argued that telemedicine may overcome disparities for rural and underprivileged populations (Verma 2020). Our findings suggest that telemedicine should not, by itself, be expected to correct health care disparities. This is especially important as increased telemedicine utilization is expected to persist beyond the COVID-19 pandemic (RAND Review 2020). Policymakers should take steps to overcome the new digital divide. Our results suggest that expanded broadband access could mitigate disparities in telehealth utilization. Outreach and education efforts could facilitate technology adoption among the elderly and the poor.

Increased telehealth adoption provides an opportunity for health systems to expand their markets and creates opportunities for new entrants, such as Amazon Care and Amwell, to provide digital healthcare services. Managers may use this technology to enter new markets and serve a broader patient base. This could increase competition and access for sophisticated and well-insured (i.e., affluent) patients. New entry might also increase access for previously undertreated patients in rural and low-income communities.

Lastly, we contribute to the theoretical understanding of the switch to digital services and its creation of a digital divide. Digital services are being used extensively (e.g., health and education) during the pandemic as communities try to enforce social distancing.[9] We identify three reasons that

[9] Anecdotal evidence indicates a similar digital divide in the provision of online education for primary and secondary school students.

could cause this digital divide. First, a community's technological infrastructure facilitates digital connections between patients and providers. The absence of broadband services will create a digital barrier for accessing healthcare services. Second, a digital divide may emerge due to older users lacking the human capital required to access digital services. This dovetails with existing research indicating that older workers adopt information technologies slower than their younger colleagues (age biased technological change) (e.g., Aubert et al. 2006). Here too, a digital divide may appear between users who can leverage their human capital to access digital services versus those who are unable to do the same. Third, health systems may prioritize established patients for the use of their digital services. Patients who do not have a prior relationship with a health system are slower to adopt telemedicine. A digital divide could be created between those with established care relationships and those who currently fall outside of the health care system.

Our study is not without limitations. First, our analysis is based on data from a single state before July 2020. Hospitals may have targeted telemedicine to underserved communities after the end of our panel. This is an open empirical question that can be examined in future research. Second, our data only capture patients with health insurance. These data have limited detail on patient race, ethnicity, and other social determinants of health. The pandemic's incidence and health consequences have been especially severe for minority populations, and further research is needed to understand telemedicine utilization in these populations. Limitations notwithstanding, our findings expand our understanding of telemedicine utilization, disparities in its provision, and its role in fighting the pandemic.

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FIGURES

Figure 1

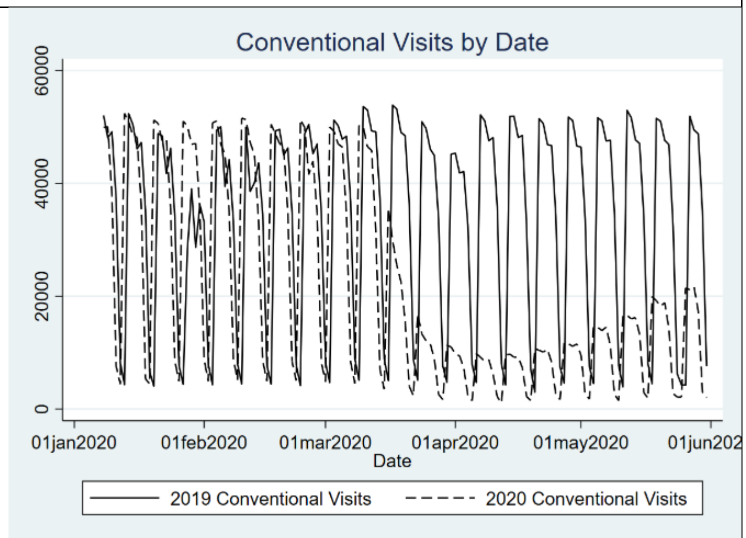
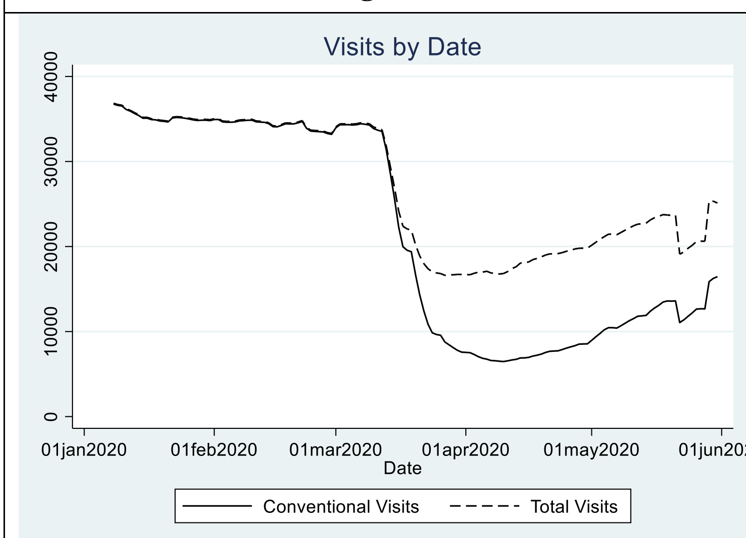


Figure 2



TABLES

Table 1: Summary Statistics				
Table1: Summary Statistics	**Prior to COVID**		**After COVID**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Conversion Rate**	.001	.015	.267	.138
Average Income	70.954	41.059	71.517	41.653
Rural	0.092	0.289	0.086	0.280
Black Proportion	0.101	0.178	0.105	0.181
Broadband access (%)	80.945	9.772	81.130	9.761
New COVID Cases/day	0.122***	0.961	62.725	110.698
Age	41.683	23.047	42.652	21.514
New Patient Visits, proportion	0.148	0.355	0.179	0.383
Established Patient Visits, proportion	0.635	0.482	0.603	0.489
Switching system visits, proportion	0.218	0.413	0.219	0.413
Cancer	0.056	0.230	0.055	0.228
COPD	0.047	0.212	0.045	0.206
Diabetes	0.113	0.317	0.114	0.317
Renal Failure	0.029	0.167	0.026	0.160
Immune deficiency	0.018	0.133	0.019	0.135
HCC Count	0.263	0.621	0.258	0.607
Visits	1,950,732		1,648,324	

**Note that these statistics describe 2020 data and exclude the interim period.*

***Summary statistics for conversion rate calculated after data are aggregated by zip code and date. Summary statistics for other variables calculated using disaggregated data.*

****Note that there are a handful of COVID cases in the pre-COVID period. Although the first COVID case in Michigan was confirmed on March 10th, subsequent investigation found Michigan's earliest infections likely occurred by March 4th or earlier.*

Table 2: Changes in Telemedicine Utilization, Selected Parameters					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Base Model	Rural	Income	Race	Broadband & COVID cases
Post COVID Indicator	0.2893***	0.2962***	0.2837***	0.2881***	0.2938***
	(0.0028)	(0.0029)	(0.0027)	(0.0029)	(0.0044)
Post COVID Indicator * Rural		-0.0802***			
		(0.0047)			
Post COVID Indicator * Average Income			0.0005***		
			(0.0001)		
Post COVID Indicator * Black				0.0440***	
				(0.0129)	
Post COVID Indicator * Broadband					0.2399***
					(0.0278)
COVID Cases					0.0001***
					(0.0000)
Observations	117,119	117,119	117,119	117,119	116,752
R-squared	0.8738	0.8791	0.8776	0.8744	0.8835
Level of Aggregation	Zip code, Date	Zip code, Date	Zip code, Date	Zip code, Date	Zip code, Date
Fixed Effects	Zip code	Zip code	Zip code	Zip code	Zip code
Clustering of Errors	Zip code	Zip code	Zip code	Zip code	Zip code

**** p<0.001, ** p<0.01, * p<0.05*

Table 3. Changes in Conventional Care Utilization, Selected Parameters					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Base Model	Rural	Income	Race	Broadband & COVID cases
Post COVID Indicator	-0.7119***	-0.7159***	-0.7084***	-0.7126***	-0.6809***
	(0.0028)	(0.0028)	(0.0027)	(0.0028)	(0.0028)
Post COVID Indicator * Rural		0.0458***			
		(0.0076)			
Post COVID Indicator * Average Income			-0.0003***		
			(0.0001)		
Post COVID Indicator * Black				0.0252*	
				(0.0104)	
Post COVID Indicator * Broadband					-0.1383***
					(0.0290)
COVID Cases					-0.0004***
					(0.0000)
Observations	117,119	117,119	117,119	117,119	116,752
R-squared	0.8982	0.8985	0.8985	0.8983	0.9039
Level of Aggregation	Zip code, Date	Zip code, Date	Zip code, Date	Zip code, Date	Zip code, Date
Fixed Effects	Zip code	Zip code	Zip code	Zip code	Zip code
Clustering of Errors	Zip code	Zip code	Zip code	Zip code	Zip code

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 4: Changes in Care Utilization for Patient Subpopulations, by Established Source of Care and Age Categories, Selected Parameters				
	(1)	(2)	(3)	(4)
	Established Care Relationships		Patient Age Categories	
VARIABLES	Telemedicine	Conventional	Telemedicine	Conventional
Post COVID Indicator	0.2330***	-0.6328***	0.2477***	-0.6836***
	(0.0126)	(0.0387)	(0.0140)	(0.0318)
Post COVID Indicator * Established, own system	0.1144***	-0.1234***	0.1394***	-0.1786***
	(0.0189)	(0.0408)	(0.0179)	(0.0293)
Post COVID Indicator * Established, other system	-0.0255	-0.1219	-0.0081	-0.1250
	(0.0194)	(0.1436)	(0.0177)	(0.1019)
Post COVID Indicator * 45<= Age < 65			-0.0127	0.1677***
			(0.0169)	(0.0458)
Post COVID Indicator * 65<= Age < 75			-0.1096***	0.2249***
			(0.0183)	(0.0427)
Post COVID Indicator * 75<= Age			-0.1756***	0.2601***
			(0.0191)	(0.0447)
Observations	651,409	651,409	889,133	889,133
R-squared	0.6121	0.5628	0.6127	0.5946
Aggregation Level	*HSECD*	*HSECD*	*HSECAD*	*HSECAD*
Fixed Effects Level	*HSEC*	*HSEC*	*HSECA*	*HSECA*
Clustering of Errors	*HSEC*	*HSEC*	*HSECA*	*HSECA*

HSEC – Health System Established Care. HSECD – Health System, Established Care, Date. HSECA – Health System* Established Care* Age Category. HSECAD – Health System, Established Care, Age Category, Date.*
**** p<0.001, ** p<0.01, * p<0.05*

Table 5: Changes in Telemedicine Utilization for Patients with COVID-Related Comorbidities						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Cancer	COPD	Diabetes	Renal Failure	Immune Deficiencies	CM Count
Post COVID Indicator	0.2008***	0.2048***	0.2312***	0.2030***	0.1885***	0.2326***
	(0.0152)	(0.0122)	(0.0176)	(0.0117)	(0.0113)	(0.0124)
Post COVID Indicator * Cancer	-0.0897***					
	(0.0200)					
Post COVID Indicator * COPD		-0.0906***				
		(0.0195)				
Post COVID Indicator * Diabetes			-0.0732***			
			(0.0188)			
Post COVID Indicator * Renal Failure				-0.0804***		
				(0.0222)		
Post COVID Indicator * Immune deficiency					0.0189	
					(0.0375)	
Post COVID Indicator * 1 CM						-0.0373*
						(0.0170)
Post COVID Indicator * 2 CM						-0.0644**
						(0.0213)
Post COVID Indicator * 3+ CM						-0.0625**
						(0.0218)
Observations	355,994	357,890	384,113	341,557	331,911	841,467
R-squared	0.4596	0.4582	0.4613	0.4568	0.4539	0.4039
Aggregation Level	*HSECD*, Cancer	*HSECD*, COPD	*HSECD*, Diabetes	*HSECD*, RF	*HSECD*, Immune	*HSECD*, CM Count
Fixed Effects Level	*HSEC* * Cancer	*HSEC* * COPD	*HSEC* * Diabetes	*HSEC* * RF	*HSEC* * Immune	*HSEC* * CM Count
Level of Clustering	*HSEC* * Cancer	*HSEC* * COPD	*HSEC* * Diabetes	*HSEC* * RF	*HSEC* * Immune	*HSEC* * CM Count

*CM – Comorbidities. HSECD – Health System, Established Care, Date. HSEC – Health System * Established Care. RF – Renal Failure. Robust standard errors. Selected parameters. *** $p<0.001$, ** $p<0.01$, * $p<0.05$*

Table 6: Changes in Conventional Care Utilization for Patients with Comorbidities, Selected Parameters						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Cancer	COPD	Diabetes	Renal Failure	Immune Deficiency	CM Count
Post COVID Indicator	-0.2438***	-0.2303***	-0.2655***	-0.2289***	-0.2223***	-0.6276***
	(0.0284)	(0.0234)	(0.0214)	(0.0196)	(0.0219)	(0.0360)
Post COVID Indicator * Cancer	0.0776**					
	(0.0278)					
Post COVID Indicator * COPD		0.0569*				
		(0.0280)				
Post COVID Indicator * Diabetes			0.0533*			
			(0.0259)			
Post COVID Indicator * Renal Failure				0.0268		
				(0.0294)		
COVID * Immune Deficiency					0.0074	
					(0.0356)	
Post COVID Indicator * 1 CM						0.1748***
						(0.0391)
Post COVID Indicator * 2 CM						0.1697***
						(0.0354)
Post COVID Indicator * 3+ CM						0.1535***
						(0.0327)
Observations	355,994	357,890	384,113	341,557	331,911	841,467
R-squared	0.5153	0.5009	0.5423	0.5078	0.5065	0.3255
Aggregation Level	*HSECD*, Cancer	*HSECD*, COPD	*HSECD*, Diabetes	*HSECD*, RF	*HSECD*, Immune	*HSECD*, CM Count
Fixed Effects Level	*HSEC* * Cancer	*HSEC* * COPD	*HSEC* * Diabetes	*HSEC* * RF	*HSEC* * Immune	*HSEC* * CM Count
Level of Clustering	*HSEC* * Cancer	*HSEC* * COPD	*HSEC* * Diabetes	*HSEC* * RF	*HSEC* * Immune	*HSEC* * CM Count

*CM – Comorbidities. HSECD – Health System, Established Care, Date. HSEC – Health System, Established Care. RF – Renal Failure. Robust standard errors. *** p<0.001, ** p<0.01, * p<0.05*

Supplementary Materials for

Does Telemedicine Transcend Disparities or Create a Digital Divide? Evidence from the COVID-19 Pandemic

ROBUSTNESS TESTS

Parallel Trends Assumption

Testing the parallel trends assumption is critical for a difference-in-differences identification strategy (Angrist and Pischke 2008). Figures 1 and 2 in our main paper indicate a near-perfect concordance in the amount of care provided on a daily basis up to March 2019 and 2020. We test this relationship empirically using a relative time model (Autor et al. 2003). We modify Equation 1 to include indicators for pre- and post-pandemic periods:

$$\frac{\Delta Telemed_{mt}}{Visits_{mt-\tau}} = \beta_0 + \sum_{n=-30}^{30} \alpha_{ni}\beta_n^{'} + \gamma X_{mt} + \mu_m + \epsilon_{mt}, \qquad (1)$$

where α_{ni} is a binary indicator for each date preceding March 4th 2020 and following March 24th 2020. If our model is properly identified, then $\beta_n \approx 0\ (\forall\, n < 0)$. This finding would suggest that unobserved and time-varying differences between the 2019 and 2020 samples would be close to zero preceding March 4th. Results in Table A1 depict the pre- and post-COVID differences in the telemedicine conversion rate by date. Coefficients in the pre-COVID column are all precisely estimated and close to zero. Even with the largest pre-COVID parameters (from February 24 through 28), we can reject differences greater than 0.06 percentage points. This demonstrates that the magnitude of any potential bias is minuscule compared with our post-COVID conversion rate of approximately 28.9 percentage points (see Table 2, Model 1). It is worth noting that 9 of the 28 pre-COVID parameters are significantly different from zero. These differences occur on a seven-day cycle suggesting that smoothing does not perfectly address seasonality. The magnitudes of these parameters are precisely estimated and extremely close to zero, bounded by -0.001 percentage points, and irrelevant.[1]

Inclusion of Market Specific Time Trends

Although the switch to telemedicine is due to a large exogenous shock arising from COVID-19 and Michigan's stay at home orders, we nevertheless utilize a more demanding empirical specification to test for the presence of market (zip code) level trends (Angrist and Pischke 2008). These might be important if local trends in telemedicine adoption were correlated with the pandemic or its response. We allow for this by interacting a linear time trend with each zip code. Results are presented in table A2 and are consistent with our main findings. These results complement specifications that allow for local variation in the timing and incidence of COVID-19 cases. In each case, we found that although local variation in COVID-19 cases was correlated with telemedicine utilization, the magnitude was extremely small and had almost no impact on the parameters of interest.

Serial Correlation of Errors

Bertrand et al. (2004) argue that errors are often correlated over time in a difference-in-difference model. This may bias our standard errors and force us to falsely accept the Null hypothesis of no increase in telemedicine utilization during COVID. However, a simple examination of Figures 2 in

[1] These small seasonal deviations could almost certainly be eliminated by including an interacted set of 2019 and 2020 day-of-week indicators.

the main paper and A1 in this appendix demonstrates telemedicine's significant increase during the pandemic period. We also find that our conclusions are robust to aggregating our day-specific observations into a single pre-COVID observation and a single post-COVID observation (Table A3).

EMPIRICAL EXTENSIONS

Temporal Heterogeneity in Telemedicine Utilization

Health systems may have required time to develop telemedicine strategies and virtual care needs may have changed across time. This might be especially important if the initial response focused on a backlog of established patients. We examine this hypothesis by allowing our parameter estimates to vary over the Post-COVID period. We divide the post-COVID period into two. The first part is 'early COVID', which is defined as the period before May 1st 2020. The latter period is the 'late COVID' which is between May 1st and June 14th. Results presented in Table A4 indicate that the magnitudes of coefficients are generally consistent over the duration of our panel.

TABLES

Table A1: Relative Time Model						
Pre-COVID differences				**Post-COVID differences**		
Date	**Estimates**	**Standard Errors**		**Date**	**Estimates**	**Standard Errors**
02/03/2020 or before	-0.0004***	(0.0002)		03/25/2020	0.2130***	(0.0029)
02/04/2020	-0.0001	(0.0002)		03/26/2020	0.2161***	(0.0030)
02/05/2020	-0.0001	(0.0002)		03/27/2020	0.2337***	(0.0029)
02/06/2020	-0.0001	(0.0002)		03/28/2020	0.2506***	(0.0030)
02/07/2020	0.0001	(0.0002)		03/29/2020	0.2653***	(0.0031)
02/08/2020	-0.0010***	(0.0002)		03/30/2020	0.2841***	(0.0031)
02/09/2020	-0.0012***	(0.0003)		03/31/2020	0.2958***	(0.0033)
02/10/2020	-0.0001	(0.0002)		04/01/2020	0.2987***	(0.0035)
02/11/2020	-0.0002	(0.0002)		04/02/2020	0.2991***	(0.0035)
02/12/2020	-0.0002	(0.0002)		04/03/2020	0.3116***	(0.0035)
02/13/2020	-0.0001	(0.0002)		04/04/2020	0.3137***	(0.0035)
02/14/2020	-0.0003	(0.0002)		04/05/2020	0.3094***	(0.0034)
02/15/2020	-0.0009***	(0.0002)		04/06/2020	0.3089***	(0.0031)
02/16/2020	-0.0009***	(0.0002)		04/07/2020	0.2996***	(0.0030)
02/17/2020	-0.0002	(0.0002)		04/08/2020	0.2954***	(0.0029)
02/18/2020	-0.0003*	(0.0002)		04/09/2020	0.2964***	(0.0029)
02/19/2020	-0.0003	(0.0002)		04/10/2020	0.2994***	(0.0029)
02/20/2020	-0.0003	(0.0002)		04/11/2020	0.3030***	(0.0030)
02/21/2020	-0.0002	(0.0002)		04/12/2020	0.3066***	(0.0030)
02/22/2020	-0.0008***	(0.0002)		04/13/2020	0.3138***	(0.0028)
02/23/2020	-0.0012***	(0.0003)		04/14/2020	0.3216***	(0.0029)
02/24/2020	0.0002	(0.0002)		04/15/2020	0.3267***	(0.0029)
02/25/2020	0.0002	(0.0002)		04/16/2020	0.3259***	(0.0030)
02/26/2020	0.0002	(0.0002)		04/17/2020	0.3307***	(0.0030)
02/27/2020	0.0002	(0.0002)		04/18/2020	0.3315***	(0.0031)
02/28/2020	0.0000	(0.0002)		04/19/2020	0.3346***	(0.0033)
02/29/2020	-0.0006***	(0.0002)		04/20/2020	0.3383***	(0.0032)
03/01/2020	-0.0014***	(0.0002)		04/21/2020	0.3405***	(0.0032)
03/02/2020	-0.0001	(0.0001)		04/22/2020	0.3383***	(0.0032)
03/03/2020	Omitted			04/23/2020 or after	0.2827***	(0.0030)

Observations: 117,119; R-squared: .9228; Level of Aggregation: Zip code, Date; Fixed Effects: Zip code
*Results based on a single model that has been broken into two columns for space considerations. Coefficients charted in Figure A1. We control for the presence of a polar vortex. *** p<0.001, ** p<0.01, * p<0.05*

Table A2: Changes in Telemedicine Utilization following COVID with Market Specific Time Trends						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Base Model	Rural	Income	Race	Broadband & COVID cases	Established Patients
Post COVID Indicator	0.3507***	0.3564***	0.3164***	0.3433***	0.1987***	0.3051***
	(0.0031)	(0.0032)	(0.0054)	(0.0035)	(0.0226)	(0.0203)
Post COVID Indicator * Rural		-0.0673***				
		(0.0068)				
Post COVID Indicator * Average Income			0.0005***			
			(0.0001)			
Post COVID Indicator * Black				0.0715***		
				(0.0126)		
Post COVID Indicator * Broadband					0.1801***	
					(0.0279)	
COVID Cases					0.0000**	
					(0.0000)	
Post COVID Indicator * Established, own system						0.1251***
						(0.0323)
Post COVID Indicator * Established, other system						-0.0326
						(0.0306)
Observations	117,114	117,114	117,114	117,114	107,197	651,409
R-squared	0.9182	0.9182	0.9282	0.9188	0.9215	0.7991
Level of Aggregation	Zip code, Date	Zip code, Date	Zip code, Date	Zip code, Date	Zip code, Date	*HSECD*
Clustering of Errors	Zip code	Zip code	Zip code	Zip code	Zip code	*HSEC*

HSEC – Health System Established Care. HSECD – Health System, Established Care, Date.*
*We control for the presence of a polar vortex. *** p<0.001, ** p<0.01, * p<0.05*
Results for age and HCCs similar and available on request

Table A3: Model Estimates with Data Collapsed to Single Pre- and Post-COVID Period, Robustness to Autocorrelation						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Base Model	Rural	Income	Race	Broadband & COVID cases	Established Patients
Post COVID Indicator	0.2777***	0.2866***	0.2426***	0.2722***	0.0490*	0.2339***
	(0.0029)	(0.0029)	(0.0063)	(0.0032)	(0.0235)	(0.0104)
Post COVID Indicator * Rural		-0.0936***				
		(0.0045)				
Post COVID Indicator * Average Income			0.0005***			
			(0.0001)			
Post COVID Indicator * Black				0.0549***		
				(0.0132)		
Post COVID Indicator * Broadband					0.0026***	
					(0.0003)	
COVID Cases					0.0003***	
					(0.0000)	
Post COVID Indicator * Established, own system						0.1034***
						(0.0155)
Post COVID Indicator * Established, other system						-0.0348*
						(0.0149)
Observations	2,202	2,202	2,202	2,202	2,168	37,050
R-squared	0.9560	0.9649	0.9609	0.9571	0.9692	0.6050
Level of Aggregation	*ZPPC*	*ZPPC*	*ZPPC*	*ZPPC*	*ZPPC*	*HSECPPC*
Clustering of Errors	Zip code	Zip code	Zip code	Zip code	Zip code	*HSEC*

ZPPC – Zip Code, Pre/Post COVID. HSECPPC – Health System, Established Care, Pre/Post COVID. HSEC - HSEC – Health System Established Care*
**** p<0.001, ** p<0.01, * p<0.05*
Results for age and HCCs similar and available on request

Table A4 Panel A: Temporal Heterogeneity in the Utilization of Telemedicine			
	(1)	(2)	(3)
VARIABLES	Base Model	Rural	Income
Early COVID	0.3080***	0.3144***	0.3024***
	(0.0027)	(0.0028)	(0.0027)
Later COVID	0.2727***	0.2801***	0.2672***
	(0.0031)	(0.0032)	(0.0030)
Early COVID * Rural		-0.0741***	
		(0.0049)	
Later COVID * Rural		-0.0855***	
		(0.0052)	
Early COVID * Avg. Income			0.0005***
			(0.0001)
Later COVID * Avg. Income			0.0005***
			(0.0001)
Observations	117,119	117,119	117,119
R-squared	0.8816	0.8870	0.8854
Level of Aggregation	Zip code, Date	Zip code, Date	Zip code, Date
Fixed Effects	Zip code	Zip code	Zip code
Clustering of Errors	Zip code	Zip code	Zip code

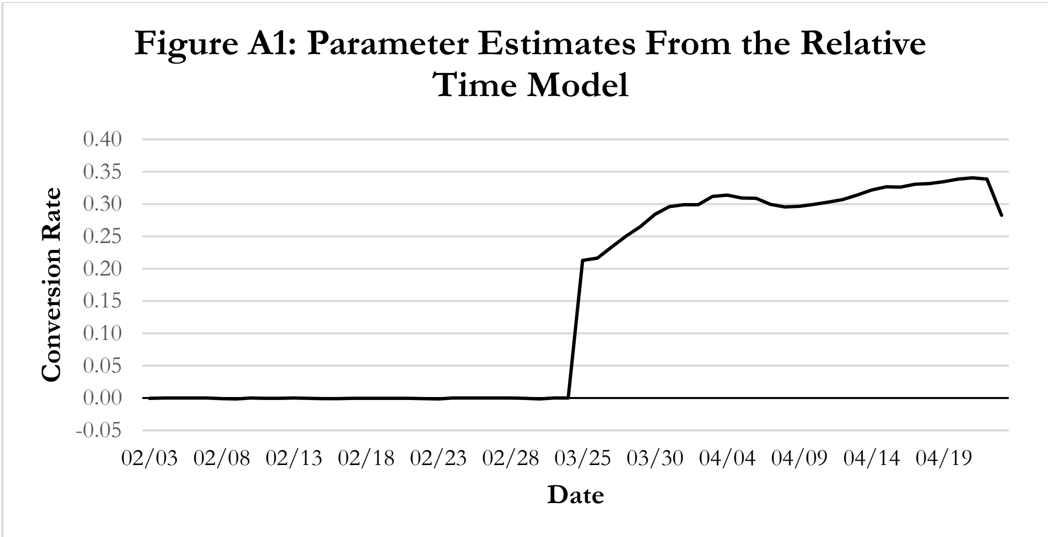
HSEC – Health System Established Care. HSECD – Health System, Established Care, Date.* Established 1 - Established, own system. Established 2 - Established, other system.

*We control for the presence of a polar vortex. *** p<0.001, ** p<0.01, * p<0.05*

Table A4 Panel B: Temporal Heterogeneity in the Utilization of Telemedicine			
	(1)	(2)	(3)
VARIABLES	Race	Broadband & COVID Cases	Established Patients
Early COVID	0.3066***	0.1455***	0.2568***
	(0.0028)	(0.0212)	(0.0148)
Later COVID	0.2717***	0.0773***	0.2128***
	(0.0031)	(0.0264)	(0.0120)
Early COVID * Black	0.0516***		
	(0.0120)		
Later COVID * Black	0.0373***		
	(0.0143)		
Early COVID * Broadband		0.2164***	
		(0.0256)	
Later COVID * Broadband		0.2594***	
		(0.0324)	
COVID Cases		-0.0009***	
		(0.0002)	
Early COVID * COVID Cases		0.0010***	
		(0.0002)	
Later COVID * COVID Cases		0.0016***	
		(0.0002)	
Early COVID * Established, own system			0.1179***
			(0.0224)
Late COVID * Established, own system			0.1105***
			(0.0182)
Early COVID * Established, other system			-0.0279
			(0.0223)
Late COVID * Established, other system.			-0.0231
			(0.0184)
Observations	117,119	116,752	651,409
R-squared	0.8823	0.8877	0.6159
Level of Aggregation	Zip code, Date	Zip code, Date	*HSECD*
Fixed Effects	Zip code	Zip code	*HSEC*
Clustering of Errors	Zip code	Zip code	*HSEC*

HSEC – Health System Established Care. HSECD – Health System, Established Care, Date.* Established 1 -
*We control for the presence of a polar vortex. *** p<0.001, ** p<0.01, * p<0.05*
Results for age and HCCs similar and available on request

FIGURES



Date format on the horizontal axis is mm/dd/2020. Data between 04/03 and 24/03 excluded (see methods in the main paper). We omit the error bars on the figure due to the negligible magnitude of standard errors. Coefficient on 04/23 is significantly smaller than other post-pandemic coefficients as it is the average of conversion rate from 04/23 to the end of our panel.

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