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THE IMPACT OF THE COVID-19 PANDEMIC AND POLICY RESPONSE ON HEALTH CARE UTILIZATION: EVIDENCE FROM COUNTY-LEVEL MEDICAL CLAIMS AND CELLPHONE DATA

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ABSTRACT

The COVID-19 pandemic has forced federal, state and local policymakers to respond by legislating, enacting, and enforcing social distancing policies. However, the impact of these policies on healthcare utilization in the United States has been largely unexplored. We examine the impact of county-level shelter in place ordinances on healthcare utilization using two unique datasets—employer-sponsored insurance for over 6 million people in the US and cell phone location data. We find that introduction of these policies was associated with reductions in the use of preventive care, elective care, and the number of weekly visits to physician offices and hospitals. However, controlling for county-level exposure to the COVID-19 pandemic reduces the impact of these policies. Our results imply that while social distancing policies do lead to reductions in healthcare utilization, much of these reductions would have occurred even in the absence of these policies.

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1. INTRODUCTION

The COVID-19 pandemic has impacted health systems and economies throughout the United States and the world. It is expected that the total economic cost of the pandemic may reach 16 trillion dollars (Cutler and Summers 2020). In the United States, policymakers have responded by enacting federal and state policies that seek to “flatten the curve” through shelter-in-place (SIP) policies that encourage social distancing. Previous research suggests that these policies had their intended effect and reduced spread of COVID-19 infection in the United States (Amuedo-Dorantes, Kaushal, and Muchow 2020; Courtemanche et al. 2020; Matrajt and Leung 2020).

However, evidence on the impacts of social distancing and SIP policies on healthcare utilization remains limited (Ziedan, Simon, and Wing 2020). In previous work, we examined changes in use of preventive healthcare services, both in-person and telemedicine visits, after the declaration of nationwide emergency in March 2020 (Whaley et al. 2020). Consistent with other studies, we find that the use of preventive and elective services declined drastically, and that the share of visits replaced by telemedicine did not fully replace the gap (Mehrotra et al. 2020). However, it is unclear from this evidence whether the decline in utilization was in response to implementation of SIP policies or due to patients’ fears of COVID-19 infection while in a healthcare facility. The effect of SIP policies on healthcare use is a priori ambiguous: While the decline in COVID-19 cases associated with these policies might instill public confidence and encourage people to seek healthcare, SIP policies might encourage the public to stay at home and avoid doctors’ offices and hospitals. If these policies do reduce necessary medical care, then, while they may limit the spread of COVID-19, they may also impose costs. If delayed or forgone care worsens patient health outcomes, then the positive COVID-related health impacts of SIP policies must be balanced with the potentially adverse consequences of SIP policies on non-

COVID care. Appropriately weighing these tradeoffs requires precise estimation of the impact of SIP policies on non-COVID care.

In this paper, we attempt to inform these tradeoffs by examining the effect of SIP polices on use of healthcare services. An important empirical challenge with evaluating the impacts of these policies is the endogenous nature of their implementation (Goodman-Bacon and Marcus 2020). While there is variation in the timing of implementation of SIP policies across counties, which can be used to identify the effects of these policies on health care utilization, counties might have implemented these policies in response to or concurrently with rising COVID cases. Therefore, it is important to disentangle the effects of SIP policies from the effects of changes in trajectory of the COVID-19 pandemic within a county. We address this potential endogeneity of SIP policies by non-parametrically controlling for the number of weeks since the first COVID-19 case and COVID-19 death in each county.

To assess the impacts of SIP policies on health services utilization, we used claims data from a nationwide sample of U.S. individuals with employer-sponsored health insurance. Our results indicate that county-level SIP policies appear to be endogenously implemented in response to COVID-19 exposure. We find large reductions in use of preventive care and elective services following the introduction of SIP policies. We find that fully controlling for variations in exposure to the COVID-19 pandemic significantly reduces the magnitude of SIP policies on healthcare utilization. For example, when not controlling for variations in COVID-19 exposure SIP policies are associated with an 82% reduction in the use of mammograms. Adding COVID-19 controls for the number of weeks since the first COVID-19 case and death within a county reduces the impact of SIP policies on use of mammograms to 16%. We find similar reductions for other forms of preventive (e.g., colonoscopy screenings and infant immunizations) and elective care (e.g., MRIs, musculoskeletal surgery, and cataract surgery). In contrast, we find small changes in non-elective care (chemotherapy and angiograms) and no change in labor and delivery rates. Thus, while use of health services has declined during the COVID-19 pandemic, the decline is not due solely to SIP policies. Instead, variation in reductions in care are driven by both the implementation of SIP policies and variations in the intensity of the COVID-19 pandemic across counties. Our results imply that while SIP policies do lead to reductions in preventive and elective care, much of these reductions would have occurred even in the absence of these policies. We confirm our main findings by using cellphone data on visits to physicians and hospitals that allow for a longer duration of follow-up post implementation of SIP policies.

Additionally, we examine changes in telemedicine and in-person office visits because many providers have shifted towards telemedicine services during the pandemic, based on recommendations from Centers for Disease Control and Prevention (CDC) (Centers for Disease Control and Prevention 2020). For example, over 9 million Medicare beneficiaries have received a telemedicine service during the public health emergency, mid-March through mid-June (Verma 2020). Similarly, between March 2 and April 14, 2020, telemedicine visits increased from 102.4 daily to 801.6 daily at NYU Langone Health (Mann et al. 2020). Data from four national telehealth providers showed a 154 percent increase in telehealth visits during the last week of March 2020 compared to the same period in 2019 (Koonin et al. 2020). Consistent with the existing literature, we also find that even after controlling for variations in the intensity of the COVID-19 pandemic, the implementation of SIP policies led to a 35% reduction in the use of office-based clinician visits and a 100% increase in the use of telemedicine. However, the absolute change in telemedicine only offset 29% of the reduction in office-based clinician visits. Our results echo previous work which has also confirmed that telemedicine visits have not fully replaced office-based visits (Ziedan, Simon, and Wing 2020). Analysis of employer-based claims data indicates that patients living in zip codes with lower-income or majority racial/ethnic minority populations experienced smaller reductions in in-person visits but also had lower rates of adoption of telemedicine (Whaley et al. 2020).

We believe that these results have several important implications for public policy. First, our finding that necessary care has been delayed suggests that additional policies designed to restore avoided care may be required. A concern echoed by other studies (Jain and Santhosh 2020; Ziedan, Simon, and Wing 2020; Czeisler 2020). Second, for some patients, delaying necessary care could have potential adverse health impacts in the future. These non-COVID-19 health impacts are currently not fully accounted for in the health impacts of the COVD-19 pandemic nor the impact of SIP policies (Woolf et al. 2020). These impacts are also not a major focus in the current discussion on the impact of the pandemic on healthcare disparities despite the fact deferred care is happening disproportionately in some populations (Czeisler 2020). Third, the pandemic, SIP policies and their associated decline in utilization might also affect the supply side of the market. For example, the decline in utilization of care is expected to have severe impacts on healthcare provider finances (Farr 2020). This is in stark contrast to insurers where lower use of health care will improve their profitability putting them in a strong financial position to withstand COVID-19 (Lucia et al. 2020). The decline in health care utilization also seems to be impacting employment in the health care industry. Himmelstein and Woolhander (2020) using the Bureau of Labor Statistics data found that the number of ambulatory workforce fell by 1.19 million persons, a 14.9% drop and the number of hospital employees decreased by 135, 000 (2.6% decline) (Himmelstein and Woolhandler 2020). Finally, we use real time cellphone mobility data on weekly visits to offices of physicians and hospitals to confirm the results of the detailed claims data. This is an important finding given that it suggests that regulators, healthcare providers, and health departments can use these types of data to make more rapid decisions on public health interventions.

The rest of the paper proceeds as follows. First, we outline the data sources and measures used in the present study. Second, we define the methods used for evaluating the impact county-level SIP policies on county-level healthcare utilization. Third, we report the results. Finally, we contextualize the results within the broader literature and present policy implications.

2. DATA

2.1. Medical Claims Data

Our primary source of data on healthcare utilization comes from weekly aggregates of medical claims data collected by Castlight Health in 2019 and 2020. Castlight provides price transparency and health benefits to self-insured employers. As part of operating these services, Castlight receives medical claims data for all employees and beneficiaries of their employer customers. The customers vary in both size—ranging from 500 to 50,000 individuals—and in industry—including manufacturing, education, and financial services. The data covers all U.S. states and the District of Columbia.

We obtained de-identified information on the number of patients, number of claims, and spending for common preventive care (colonoscopies for persons ages 46 to 64, mammograms for women ages 46 to 64, and vaccines and immunizations for children ages two and younger), elective (MRIs, musculoskeletal surgery, and cataract surgery), and non-elective (labor and delivery, chemotherapy, and angioplasty) services. We also obtained information on patient demographics (age, and gender), geographic market (state and county), and the number of eligible members within each cell. The demographics of the Castlight sample in 2018 is similar to the American Community Survey in 2018 as exhibited in Table 1. We used this information to calculate the weekly number of patients who received each procedure per 10,000 eligible persons We similarly obtained the number of telemedicine interactions for this population.[2]

2.2. Cellphone-based Measures of Healthcare Utilization

In conjunction with medical claims data, we use data from SafeGraph as a second way to measure healthcare utilization. SafeGraph aggregates GPS pings from about 45 million mobile devices and 6 million points-of-interest (POI). The effect of this is measurements of traffic patterns, both to a large collection of POIs, and to/from residences of the users. We used the "Weekly Patterns" data from SafeGraph to quantify office-based healthcare utilization. In this dataset, for each weekly file, SafeGraph makes one row for each POI. For each POI, SafeGraph reports its geographic location, industry via the National American Industry Classification System (NAICS) code, and the total number of visitors in their mobile device panel that have visited each day. The weekly data measures begin on Monday and end the following Sunday. Since visits to each facility is a length 7 array, we are able to calculate this every day, then combine for each week for 2019 and 2020. We use the four-digit NAICS code to identify office of physicians (6211) and general medical and surgical hospitals (6221).[3] These data have been commonly used to examine the effect of COVID-19 and COVID-19 related policies on social distancing (Cronin and Evans 2020; Goolsbee and Syverson 2020; Gupta et al. 2020; Cook, Newberger, and Smalling 2020; Moreland 2020; Gao et al. 2020). To our knowledge, there are

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[2] Telemedicine procedures were identified as claims with procedure codes in the following set: ('99441','99442','99443','99444','99421','99422','99423','98970','98971','98972','G2061','G2062','G2063'), claims with a procedure code modifier in ('95','GT','GQ'), or a place of service code equal to 2.

[3] Note that our weeks which are Wednesday-Tuesday are different than SafeGraph weeks which are Monday-Sunday. This required breaking each row into seven different daily entries, then re-combining based upon our weeks. We used the Wednesday-Tuesday designation for computational reasons.

only two studies that have used the SafeGraph data to measure utilization of healthcare services, proxied by either visits to hospitals (Jay et al. 2020) or abortion clinics (Andersen, Bryan, and Slusky 2020).

2.3. Data on Social Distancing Policies

To measure county-level SIP policies, we use data collected by Cook et al. (2020). The data include SIP policies from the New York Times and local news and government websites. The authors collected the dates for statewide orders from the New York Times (The New York Times 2020). For states without a state-wide order the authors searched local news and government sites for SIP policy dates for individual counties. Counties that the authors failed to find a news report or website that contained a SIP policy were assumed to have followed the state's policy (Cook, Newberger, and Smalling 2020).

2.4. COVID-19 Cases and Deaths

We obtained the total number of COVID-19 cases and deaths for each county from USAFacts (USAFacts 2020). These data have been used in previous studies examining disparities in COVID-19 case rates (Adhikari et al. 2020; Brown and Ravallion 2020). The data are accumulated by the Centers for Disease Control and Prevention (CDC) using information from state public health websites. The data track the total number of COVID-19 cases and deaths in each county for each day. Based on these data we identified the week of the first COVID-19 case and COVID-19 death for each county.

3. ESTIMATION APPROACH

3.1. Effect of Social Distancing Policies on Healthcare Utilization

To estimate the effect of SIP on healthcare utilization, we would ideally estimate two-way fixed effects difference-in-difference models that estimate the difference in utilization following the implementation of a SIP policy. However, a key challenge of the validity of this type of approach is the endogenous nature of SIP policies, which are likely implemented in response to growth in the COVID-19 pandemic. We attempt to address this limitation by controlling for county-level variations in exposure to the COVID-19 pandemic.

Our main approach uses non-parametric controls for the duration of exposure to the COVID-19 pandemic in each county. For each county g and week t, we calculate the number of weeks since the first COVID-19 case ($caseweeks_{gt}$) and death ($deathweeks_{gt}$) in that county. We estimate a regression that includes fixed effects for each measure of COVID-19 exposure duration:

$$patients_{igt} = \alpha + \delta_1 SIP_{gt} + \sum \phi_t caseweeks_{gt} + \sum \rho_t deathweeks_{gt} + \beta_1 X_i + \tau_1 \boldsymbol{week}_t + \tau_2 \boldsymbol{year}_t + \gamma \boldsymbol{county}_g + \varepsilon_{igt} \tag{1}$$

In this model, $patients_{igt}$ represents the number of patients per 10,000 eligible members who receive each of the selected procedures. Using a dependent variable in level-terms allows for an absolute comparison in changes in utilization across procedures. To allow for a relative comparison, we also estimate models that use the log-transformed number of patients who receive each procedure. We included controls for patient demographics, age and gender, in X_i. We also include fixed effects for calendar week, year, and county. We weight each regression by the number of eligible members within each sample cell. We estimate these models using ordinary least squares and cluster standard errors at the county level.

The δ_1 coefficient measures the effect of SIP policies, indexed by SIP_{gt}, on utilization. For this coefficient to have a causal interpretation, there must not be an unobservable that changes both the implementation of policies ($policy_{gt}$) and utilization of care. Given the scope of the COVID-19 pandemic, the validity of this assumption may be challenging. In particular, changes in COVID-19 cases could lead to both implementation of policies and concerns of infection that lead to care avoidance that would have occurred even in the absence of formal policy declarations. Our controls for the duration of exposure attempt to address the potential endogeneity of SIP policies. We iteratively add these controls to assess the impacts of controlling for county-level variations in exposure to COVID-19 on the impacts of SIP policies.

We perform two additional tests to control for variations in the intensity of the COVID-19 pandemic. First, we test for differential trajectories of the COVID-19 pandemic based on county urbanicity using measures from the National Center for Health Statistics (Centers for Disease Control and Prevention 2019). We interact the fixed effects for the number of weeks since the first COVID-19 case and death in each county with indicators for whether the county is an urban or rural county, and measures of urbanicity.[4] We avoid directly controlling for the number of COVID-19 cases or deaths because both cases and deaths could be impacted by the implementation of SIP policies.

Second, we test for pre- and post-implementation trends using an event study approach. For the 13 weeks before and the 10 weeks following implementation of policy implementation, we estimate weekly differences in use of each procedure using a regression of the form

[4] The urban/rural categories include large central metropolitan area, large fringe metropolitan area, medium metropolitan area, micropolitan area, noncore area, and small metropolitan area.

$$y_{igkt} = \alpha + \sum_{l} \delta_l policy_{gl} + \beta_1 X_i + \tau \boldsymbol{week}_t + \gamma \boldsymbol{market}_g + \psi \boldsymbol{procedure}_k + \varepsilon_{igkt} \quad (2)$$

In this specification, the δ_l coefficients test the impacts of the policy in the weeks before and after implementation.

4. RESULTS

4.1. Effect of SIP policies on use of preventive, elective, and non-elective care

Figure 1 presents unadjusted trends in the use of preventive (Panel A), elective (Panel B), and non-elective care (Panel C). For each outcome, 2020 use rates are relative to the use rates in the same week in 2019. For all three care categories, we observe stable trends in January and February. Beginning in March, after the declaration of the pandemic in the US, preventive and elective care use rates decline rapidly.

While the unadjusted figures show reductions in care, they do not identify how policy responses to limit the spread of COVID-19 impacted non-COVID-19 healthcare services. Table 2 presents difference-in-difference estimates of changes in care utilization following county-level SIP policies. The unit of observation is at the week, county, gender, and age-group level.[5] For colonoscopies, the first four columns, utilization rates decreased by 3.6 per 10,000 persons following SIP laws when not controlling for the county-level COVID-19 exposure, which translates to a 89% when compared to the baseline mean utilization rate in the ninth week of 2019. Non-parametrically controlling for the weeks since the first COVID-19 case, death, and both cases and deaths substantially reduces the impact of SIP policies on colonoscopy use (rows

[5] The population for colonoscopy procedures is limited to those ages 46 to 64. Mammograms are limited to women ages 46 to 64.

2-4). In the preferred specification in column 4 that includes both sets of controls, the introduction of SIP policies lead a 0.9-person decrease in the use of colonoscopies, a relative decrease of 23%. Thus, controlling for the trajectory of the COVID-19 pandemic reduces the impact of SIP policies on colonoscopy utilization by 74%.

In the rest of Panel A, we observe similar results for the two other forms of preventive services—mammograms for women ages 46 to 64 (columns 5-8) and immunizations for children under the age of two (columns 9-12). SIP laws lead to a 17.1-person decline (82% relative reduction) in use of mammograms when not controlling for COVID-19 exposure. The effect falls by 80% to a 5.5-person reduction (16% relative reduction) when fully controlling for COVID-19 exposure. For immunizations, we find a 5.5-person reduction (23% relative reduction) when not controlling for COVID-19 exposure and no impacts of SIP policies when fully controlling for COVID-19 exposure.

SIP policies lead to similarly-sized reductions in the use of elective procedures, and the effect of SIP policies is again influenced by county exposure to the COVID-19 pandemic (Panel B). For MRIs, musculoskeletal surgery, and cataract surgery, we find absolute reductions of 1.9, 0.5, and 0.15 per 10,000 when not controlling for COVID-19 exposure, respectively. These absolute reductions translate to relative reductions of 55%, 50%, and 70% in the use of each service. However, adding the full set of COVID-19 controls reduces the impact of SIP policies on elective healthcare utilization by approximately 70%. In columns 4, 8, and 12, we find absolute reductions of 0.6, 0.1, and 0.05, which translate into relative reductions of 18%, 11%, and 25%.

For non-elective care (Panel C), we observe smaller changes following SIP policies. We do not observe changes in labor and delivery rates following SIP policies. We find a small reduction in use of chemotherapy (columns 5-8). When including the full set of COVID-19 controls, we find a 0.2-person reduction in chemotherapy rates, which translates to a 14% relative reduction. Unlike the other procedures, the effect of SIP policies is largest when including the full set of COVID-19 controls. For cardiac angiograms, we find a 34% relative reduction when not controlling for COVID-19 exposure and a 11% reduction when including the full set of COVID-19 controls.

As shown in Table 3, we find similar results when using the log-transformed number of patients with each visit. For preventive care and when fully controlling for county-level exposure to the COVID-19 pandemic, we find a 22% reduction in the use of colonoscopies,[6] a 38% reduction in mammogram use, and a 10% reduction in infant immunization rates. These effects of SIP policies are approximately 40% of the magnitude of the estimated effect when not controlling for exposure to the COVID-19 pandemic (columns 1, 5, and 9). We likewise find 12%, 6%, and 2% reductions in MRI, musculoskeletal surgery, and cataract surgery elective procedures when controlling for variations in exposure to COVID. These effects are similarly approximately 60% of the estimated effect when not controlling for the county-level intensity of the COVID-19 pandemic. For non-elective care, we find no change in labor and delivery rates and small reductions, approximately 4%, in chemotherapy and angiogram rates.

Our sensitivity test that non-parametrically controls for differing trajectories of the COVID-19 pandemic based on county-level urban vs. rural status shows similar results (Appendix Table 1 for levels and Appendix Table 2 for logs). Controlling for differential exposure to the COVID-19 pandemic using both measures of market type (urban vs. rural and categories for urbanicity) reduces the impact of SIP policies on healthcare utilization. In addition, we obtain similar results for both measures of market type.

[6] Because the dependent variable is log-transformed, the coefficients can be interpreted in percentage terms by applying $\exp(\beta) - 1$.

4.1.1. Event Study Results

We estimate event studies that examine weekly trends in the use of each procedure for the year 2020. As shown in Figure 2, the event study results are similar to the previously discussed regression results. Following the implementation of SIP policies, we observe reductions in use rates for preventive and elective care, but smaller or no change in weekly trends for non-elective care. Importantly, we do also find some evidence that the reduction in utilization occurs in the one- or two-week period prior to the implementation of a SIP policies. This immediate pre-trend suggests that, consistent with the regression results, SIP policies are implemented in response to COVID-19 exposure, which concurrently contributes to reductions in use of preventive and elective services.

4.2. Substitution of in-person office visits with telehealth visits

Similar to the procedure-level trends, Figure 3 presents unadjusted weekly trends in the use of in-person office visits and telemedicine. Through February 2020, office visit trends were stable and averaged approximately 661.2 visits per week. During this period, telemedicine visits were minimal, and averaged 2.8 calls per 10,000 patients per week. Beginning in March 2020, there is a clear reduction in in-person office visits and a corresponding spike in telemedicine use. By the end of April, in-person office visits decreased to 341.7 per 10,000 persons, relative to the year prior, an absolute reduction of 319.4 visits and a relative decrease of 48%. Use of telemedicine services increased to 87.6 per 10,000 persons, a relative increase of 3,066%. However, the absolute increase in the use of telemedicine only offsets approximately 27.4% of the decline in in-person office visits.

These descriptive findings are confirmed in the regression results presented in Table 4. Panel A presents level changes and Panel B presents log changes. In column 1, following SIP laws, use of in-person office visits declined by 107.4 persons per 10,000. The inclusion of fixed effects for the number of weeks since the first COVID-19 case within the county reduces the magnitude of the SIP policy coefficient by half to 49.3 (column 2). Including the number of weeks since the first COVID-19 death further reduces the SIP coefficient to 34.0, and including both, the preferred specification, results in a 36.6-person reduction in the use of office visits. In Panel B, when using log-transformed in-person office visits, SIP policies lead to a 55% reduction in use of in-person office visits (column 1), which decreases to a 35% reduction when including the full set of county-level COVID-19 controls (column 4).

The same factors that cause a reduction in in-person office visits also lead to an increase in telemedicine visits. SIP policies lead to a 64.2-person increase in the use of telemedicine when not controlling for variation in COVID-19 exposure, and a 10.5-person increase when adding the full set of COVID-19 controls. In relative terms (Panel B), the preferred specification in column 8 shows a 99.6% increase in the use of telemedicine, which is smaller than the estimated 766% in column 5 when not controlling for county-level COVID-19 exposure. However, the large relative shift towards telemedicine does not offset the even larger absolute reduction in in-person office visits. The difference between the absolute change coefficients in columns 4 and 8 shows that the increase in telemedicine offsets only approximately 29% of the decline in in-person office visits.

4.3. Changes in healthcare utilization using mobile tracking data

As a robustness check we estimate models using the mobile tracking data. In Appendix Figure 1 we report the unadjusted number of weekly visits to both office of physicians and hospitals in 2020. The number of weekly visits dropped drastically for physicians and hospitals after the national emergency declaration. For the regression models we obtain similar results when using mobile tracking data that measures the weekly number of visits to healthcare providers (Table 5). For physician office visits, columns 1-4, we find that weekly visits to physicians decreased by 11.8 following the introduction of SIP policies, a relative decrease of 26%. The dependent variable is weekly foot traffic to locations of individual offices of physicians. Panel B presents log-transformed visits, which can be interpreted as relative changes. Because the SafeGraph data derives from a sample approximately 10% of all cell phone users, the absolute reductions are an underestimate of the absolute changes in visits. The estimated impact of SIP laws falls considerably when controlling for the number of weeks since the first COVID-19 case and death. The preferred specification in column 4 indicates a 3.7 decrease, a relative change of 8%. The result in Panel B, a 10% reduction, is similar.

Similar patterns exist for visits to hospitals (Table 8, columns 5-8). Following the introduction of SIP policies, weekly visits to hospitals decreased by 145.8 visits per week, a relative decrease of 30%. The relative decreases in Panel B is a 23% reduction. Adding in the fixed effects that measure COVID-duration in each county reduces the magnitude of the SIP coefficient. Following the first COVID-19 case, weekly visits to hospitals decrease by 61.9 visits per week, a relative decrease of 13%. In column 8, the impact of SIP laws on weekly visits to hospitals decreases to a 49.3 absolute differences, equivalent to a 10.0% reduction off of baseline rates, and a 14% relative difference when measured in logs.

5. DISCUSSION

The COVID-19 pandemic has been an unprecedented shock to the U.S. healthcare delivery system. We found a drastic decline in preventive and elective services due to SIP policies related to the COVID-19 pandemic, but the impact of these policies is lessened when accounting for variations in exposure to the COVID-19 pandemic. These reductions in use of non-COVID care as a result of SIP policies should be weighed against potential benefits when evaluating the welfare implications of SIP policies.

Our results also suggest that the COVID-19 pandemic led to drastic reductions in use of health care. These effects were much larger than the decline in care due to SIP policies. Our estimates of decline in healthcare utilization during the early stages of the pandemic are in line with existing studies by Chatterji and Li (2020), Mehrotra and colleagues (2020) and Ziedan et al. (2020). It is important to note that our findings are during the initial stage of the pandemic, and that the length of the pandemic and mitigation strategies will define the aggregate cost on both consumers and providers (Cutler 2020). Some are concerned that the deferred care may cause some individuals with chronic conditions to become sicker and that it might increase aggregate costs (Lucia et al. 2020). This may also lead to constraints on care capacity post pandemic (Wosik et al. 2020). In addition, how the healthcare sector will be able to provide elective procedures once the pandemic has subsided is not known. Anecdotal evidence from some providers is that they will shift elective procedures to weekends (Lucia et al. 2020). Future researchers should explore this possibility and whether there are impacts on quality of care.

Our results provide a crucial first step on measuring the impact of COVID-19 on healthcare utilization based on various measures. The findings are important given that the Government Accountability Office has now pledged to track monthly changes in healthcare employment, change in volume of elective procedures across settings, median monthly changes in hospital operating margins, and changes in healthcare services as a proportion of personal consumption expenditures (Government Accountability Office 2020). The results using cellular phone geolocation data imply that these data should be considered when measuring healthcare utilization over the course of the pandemic while waiting for healthcare claims data to be released.

We also found that while there were drastic declines in in-person office visits that there was a rapid increase in telemedicine utilization. Telemedicine services have been used to maintain access and continuity of medical care (Wosik et al. 2020). However, in line with previous work, telemedicine utilization did not sufficiently replace the entire drop in in-person office visits (Mehrotra et al. 2020). Whether telemedicine use will be sustained during and following the COVID-19 pandemic remains uncertain. The uncertainty is driven in part by uncertainty if the existing policy landscape for telemedicine will be sustained as the pandemic proceeds and eventually ends (Lucia et al. 2020). For example, insurers are concerned that the increase in telemedicine may lead to increases in fraud and overutilization of services if it becomes additive over existing trends post pandemic (Lucia et al. 2020). Separately, many providers report that they do not have the technology system to make the shift to telemedicine or that in-person office visits are needed to achieve a positive health outcome (Lucia et al. 2020). These concerns should be addressed given that after the pandemic, telemedicine can serve as one way to proactively engage with patients who deferred care and to help the healthcare system manage the upcoming surge in demand for procedures unrelated to COVID-19 (Wosik et al. 2020).

This study is not without limitations. First, while we use medical claims data from a large and diverse study population that is employed, it represents a subset of individuals with private insurance and it does not include other important populations, such as patients with Medicaid, and those lacking insurance. Insurers have reported that Medicaid enrollment is increasing at a rapid rate when compared to marketplace enrollment, but surprisingly enough slower-than expected (Lucia et al. 2020). Our findings, while large, are potentially an underestimate for the declines in the number of visits and length of stay. Second, the SafeGraph mobile tracking data, comprise of approximately 10 percent of all cellphone users and 6 million locations. Thus, our results using those data are limited to that particular population and those particular locations. Our measures of number of visits are not necessarily tracking healthcare utilization, instead the number of individuals who visit locations under that particular NAICS code. Third, we are not able to examine whether care that has been deferred during the early period of the COVID-19 pandemic will be deferred until the future or avoided completely. Our estimates do not capture potential innovative approaches by providers to ensure patient resumption of preventive care. This limitation is important, given that concerted efforts are being made to increase the use of preventive services such as vaccinations which has exhibited a sharp initial drop after the national emergency declaration. Future work must monitor each of the preventive measures that we track in the present study and disparities in the use of preventive services. Fourth, the present study does not include measures of healthcare capacity. That said, a recent report by the Government Accountability Office (2020) reports that intensive care unit bed availability data is not currently up to date given that only 60 percent of hospitals have reported their information as of early June 2020 and that 95 to 100 percent are needed for effective analysis (Government Accountability Office 2020).

To our knowledge, our study is the most comprehensive to date on the effects of county-level SIP policies on healthcare utilization. We use multiple novel datasets and measures to evaluate the effect of these policies. Our results indicate that utilization has dropped drastically and that it varies by the type of care received and the severity of the COVID-19 pandemic within a county. Finally, our results indicate that while the use of telemedicine has increased, it has not fully replaced the use of office-based visits. Thus, it is critical that public policy and public health officials do more to ensure that individuals receive the care that they desperately need.

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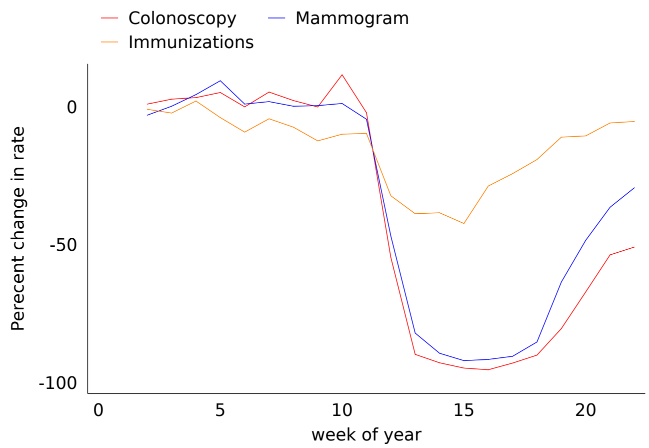
7. TABLES AND FIGURES

Table 1: Unadjusted Descriptive Statistics of Castlight Health population and American US Community Survey in 2018

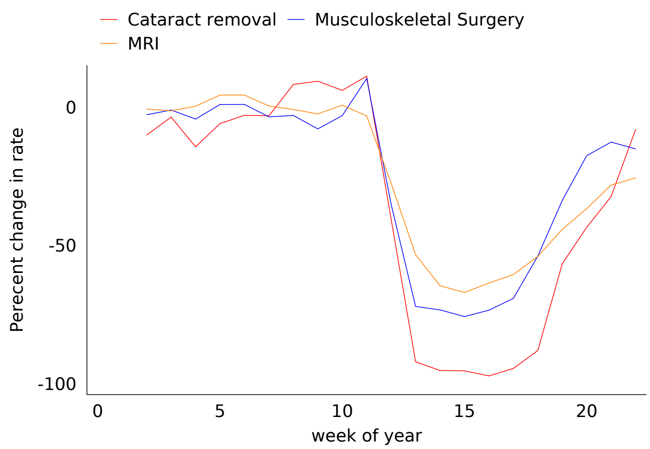
	Castlight Health (2018)	ACS (2018)
Number of enrolled persons	5,608,888	162,136,077
Gender, percent female (%)	50.0%	50.0%
Average age	34.3	33.5
Census region		
South	40.6%	35.70%
Midwest	23.0%	22.80%
Northeast	10.4%	18.20%
West	26.0%	23.40%

Figure 1: Unadjusted Trends in Healthcare Service Utilization

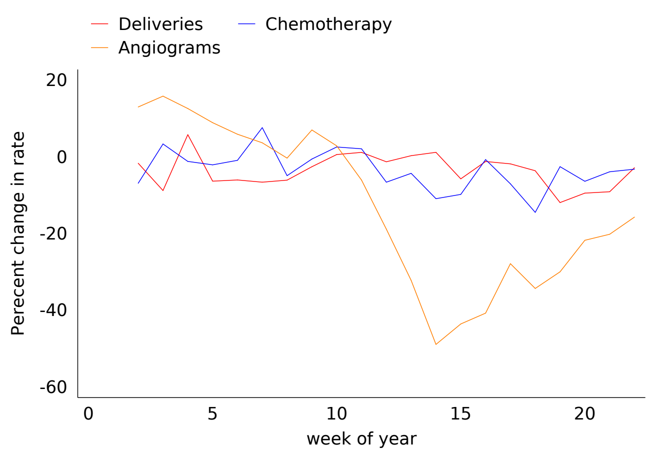
Panel A: Preventive Care



Panel B: Elective Care



Panel C: Non-Elective Care



Caption: Immunizations are restricted to those aged 2 or younger. Colonoscopy is restricted to those 46 or older. Mammograms were restricted to females aged 46 or older. Deliveries were restricted to women between the ages of 19 and 45.

Table 2: Effect of Social Distancing Policies on Preventive, Elective, and Non-Elective Procedure Utilization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Preventive Care	**Colonoscopy**				**Mammogram**				**Immunizations**			
post shelter in place	-3.642***	-1.376***	-1.112***	-0.942***	-17.69***	-5.922***	-5.303***	-3.498**	-5.458***	0.643	-0.258	1.173
	(0.767)	(0.317)	(0.243)	(0.262)	(3.152)	(1.629)	(1.227)	(1.395)	(1.248)	(2.170)	(1.336)	(2.022)
Weeks since first case FE		X		X		X		X		X		X
Weeks since first death FE			X	X			X	X			X	X
Observations	818,153	818,153	818,153	818,153	406,616	406,616	406,616	406,616	320,303	320,303	320,303	320,303
R-squared	0.705	0.728	0.717	0.732	0.780	0.795	0.787	0.799	0.886	0.889	0.888	0.890
baseline mean	4.1	4.1	4.1	4.1	21.6	21.6	21.6	21.6	22.0	22.0	22.0	22.0
Panel B: Elective Care	**MRI**				**Musculoskeletal surgery**				**Cataract surgery**			
post shelter in place	-1.882***	-0.830***	-0.628***	-0.604***	-0.548***	-0.193**	-0.159***	-0.116*	-0.148***	-0.0736**	-0.0446***	-0.0528**
	(0.390)	(0.208)	(0.118)	(0.162)	(0.124)	(0.0758)	(0.0501)	(0.0703)	(0.0354)	(0.0307)	(0.0119)	(0.0253)
Weeks since first case FE		X		X		X		X		X		X
Weeks since first death FE			X	X			X	X			X	X
Observations	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189
R-squared	0.619	0.624	0.621	0.625	0.485	0.488	0.486	0.490	0.258	0.261	0.259	0.263
baseline mean	3.3	3.3	3.3	3.3	1.1	1.1	1.1	1.1	0.2	0.2	0.2	0.2
Panel C: Non-Elective Care	**Labor and delivery**				**Chemotherapy**				**Angiograms**			
post shelter in place	0.0600	-0.107	0.0131	-0.107	-0.0558**	-0.203***	-0.155***	-0.211***	-0.213***	-0.0945**	-0.0917***	-0.0632*
	(0.106)	(0.117)	(0.0947)	(0.113)	(0.0276)	(0.0587)	(0.0333)	(0.0507)	(0.0356)	(0.0394)	(0.0186)	(0.0383)
Weeks since first case FE		X		X		X		X		X		X
Weeks since first death FE			X	X			X	X			X	X
Observations	818,342	818,342	818,342	818,342	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189
R-squared	0.554	0.555	0.555	0.555	0.550	0.550	0.550	0.550	0.440	0.440	0.440	0.441
baseline mean	1.8	1.8	1.8	1.8	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5

Caption: Baseline means are calculated based on the ninth week of 2019. Regression models were estimated using ordinary least squares. Regression models also include measures for the patient's age, gender, and county. Outcome measure is the number of patients, and all models are weighted for the total number of eligible enrollees. Standard errors are clustered at the county level. Immunizations are restricted to those aged 2 or younger. Colonoscopy is restricted to those 46 or older. Mammograms were restricted to females aged 46 or older. Deliveries were restricted to women between the ages of 19 and 45. *** p<0.01, ** p<0.05, * p<0.1

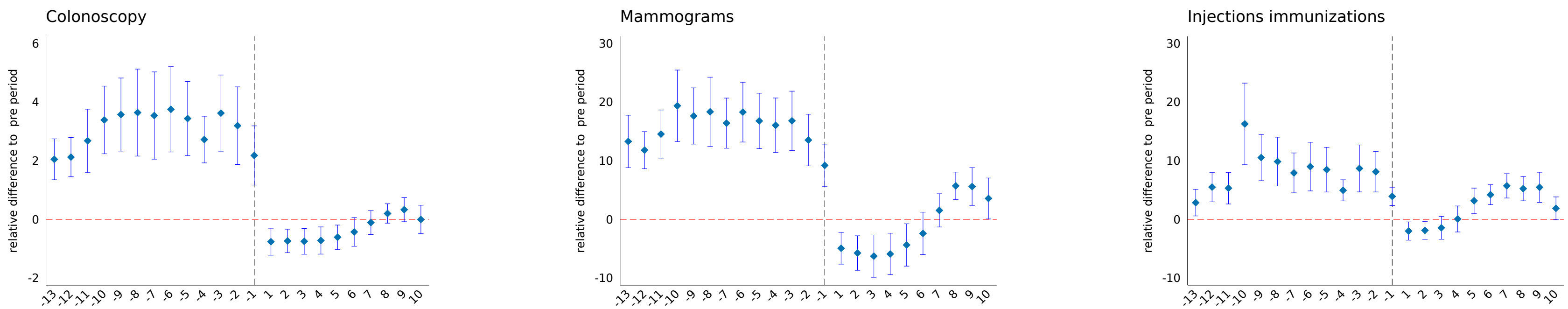
Table 3: Effect of Social Distancing Policies on Log-Transformed Preventive, Elective, and Non-Elective Procedure Utilization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Preventive Care	**Colonoscopy**				**Mammogram**				**Immunizations**			
post shelter in place	-0.745***	-0.370***	-0.296***	-0.247***	-1.002***	-0.647***	-0.587***	-0.473***	-0.156***	-0.129***	-0.126***	-0.104***
	(0.0703)	(0.0587)	(0.0342)	(0.0452)	(0.0444)	(0.0801)	(0.0402)	(0.0556)	-0.0158	-0.0245	-0.0164	-0.0241
Weeks since first case FE		X		X		X		X		X		X
Weeks since first death FE			X	X			X	X			X	X
Observations	818,153	818,153	818,153	818,153	406,616	406,616	406,616	406,616	320,303	320,303	320,303	320,303
R-squared	0.748	0.758	0.757	0.763	0.879	0.884	0.886	0.888	0.930	0.930	0.930	0.931
baseline mean	4.1	4.1	4.1	4.1	21.6	21.6	21.6	21.6	22.0	22.0	22.0	22.0
Panel B: Elective Care	**MRI**				**Musculoskeletal surgery**				**Cataract surgery**			
post shelter in place	-0.296***	-0.180***	-0.143***	-0.131***	-0.176***	-0.0958***	-0.0757***	-0.0646***	-0.0679***	-0.0337***	-0.0215***	-0.0223**
	(0.0248)	(0.0260)	(0.0150)	(0.0202)	(0.0238)	(0.0179)	(0.0128)	(0.0160)	(0.0121)	(0.0112)	(0.00519)	(0.00878)
Weeks since first case FE		X		X		X		X		X		X
Weeks since first death FE			X	X			X	X			X	X
Observations	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189
R-squared	0.719	0.720	0.720	0.721	0.551	0.552	0.552	0.553	0.297	0.300	0.299	0.301
baseline mean	3.3	3.3	3.3	3.3	1.1	1.1	1.1	1.1	0.2	0.2	0.2	0.2
Panel C: Non-Elective Care	**Labor and delivery**				**Chemotherapy**				**Angiograms**			
post shelter in place	-0.00155	-0.0164	-0.0103	-0.0195	-0.0173***	-0.0370***	-0.0333***	-0.0401***	-0.0825***	-0.0522***	-0.0494***	-0.0408***
	(0.00878)	(0.0143)	(0.0108)	(0.0138)	(0.00507)	(0.0127)	(0.00709)	(0.0113)	(0.0112)	(0.0111)	(0.00856)	(0.0115)
Weeks since first case FE		X		X		X		X		X		X
Weeks since first death FE			X	X			X	X			X	X
Observations	818,342	818,342	818,342	818,342	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189
R-squared	0.646	0.646	0.646	0.647	0.629	0.629	0.629	0.629	0.477	0.477	0.477	0.478
baseline mean	1.8	1.8	1.8	1.8	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5

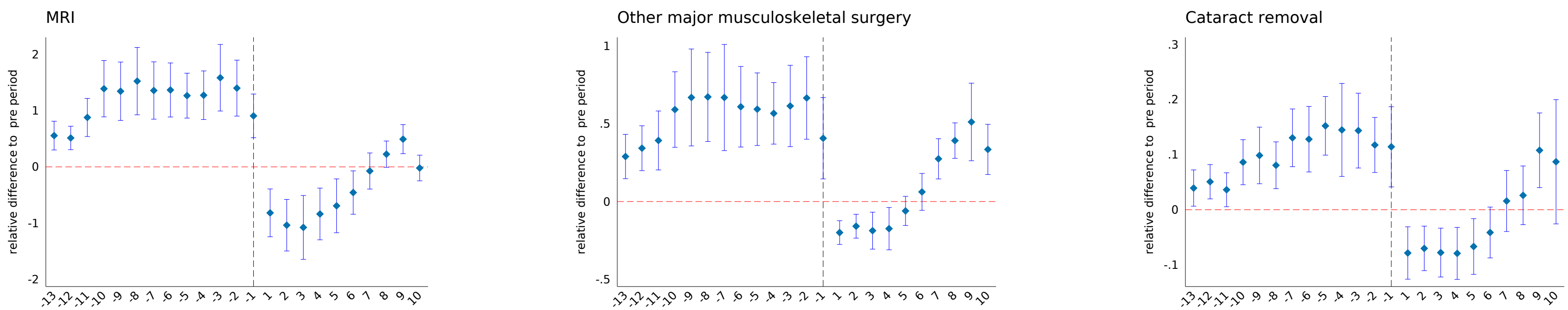
Caption: Baseline means are calculated based on the ninth week of 2019. Regression models were estimated using ordinary least squares. Regression models also include measures for the patient's age, gender, and county. Outcome measure is the natural log for the number of patients, and all models are weighted for the total number of eligible enrollees. Standard errors are clustered at the county level. Immunizations are restricted to those aged 2 or younger. Colonoscopy is restricted to those 46 or older. Mammograms were restricted to females aged 46 or older. Deliveries were restricted to women between the ages of 19 and 45. *** p<0.01, ** p<0.05, * p<0.1

Figure 2: Event Studies on Effect of Social Distancing on Preventive, Elective, and Non-Elective Procedure Utilization

Panel A: Preventive Care



Panel B: Elective Care



Panel C: Non-Elective Care

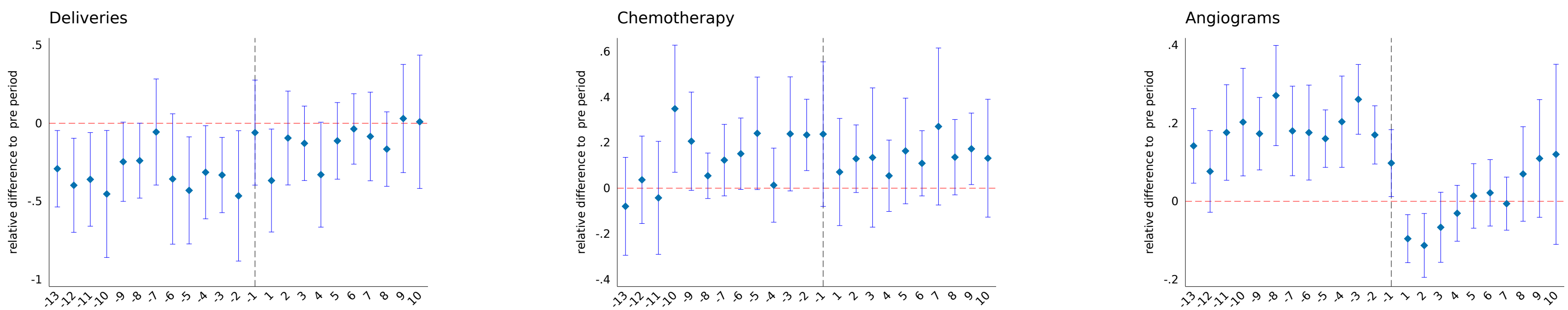


Figure 3: Unadjusted Trends in In-Person Office Visits and Telemedicine Use

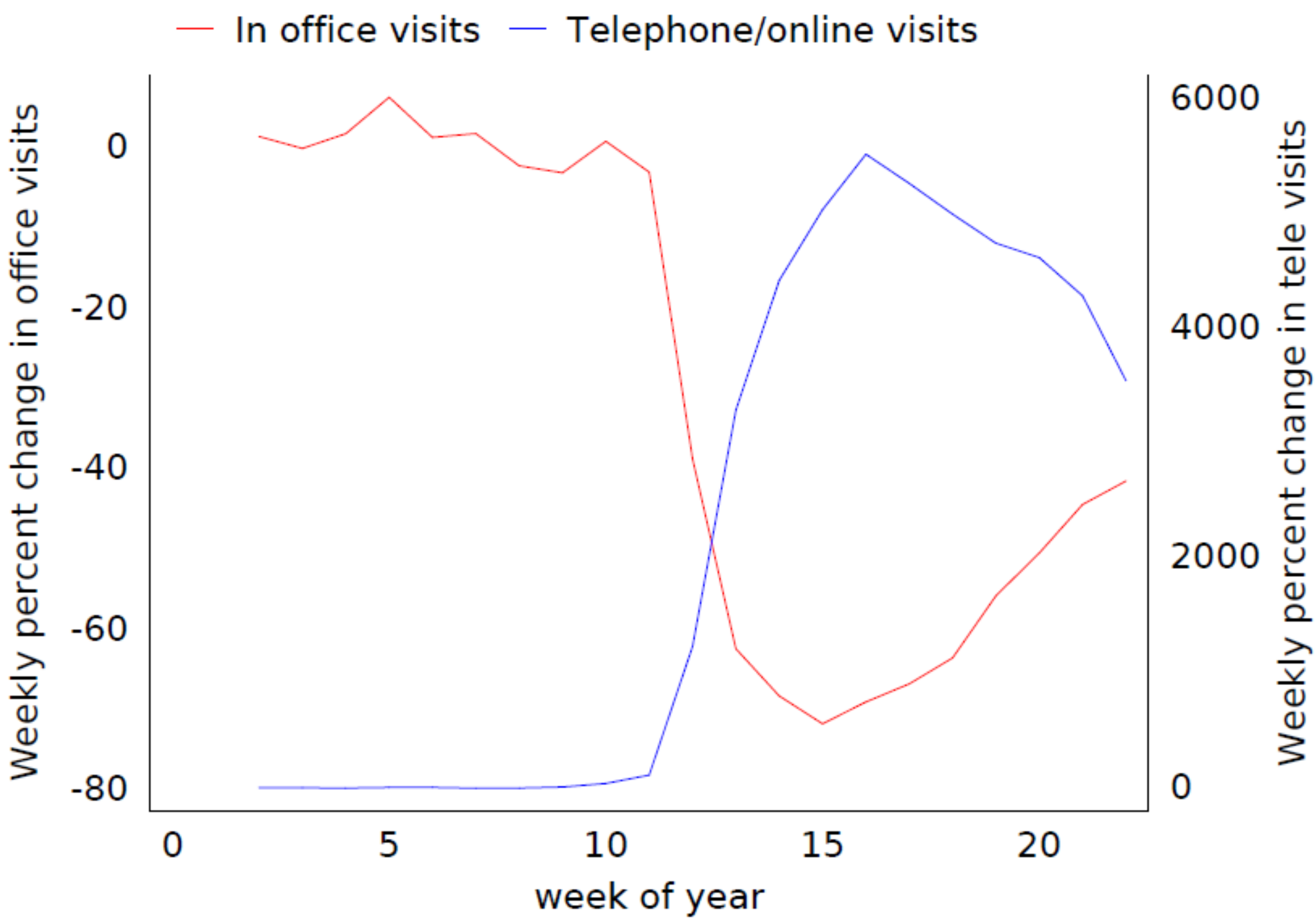


Table 4: Effect of Social Distancing Policies and COVID-19 Exposure on In-Person Office Visit and Telemedicine Utilization:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	In-person office visits				Telemedicine			
Panel A: Level changes								
post shelter in place	-107.4***	-49.30***	-34.01***	-36.62***	64.18***	17.26***	12.20***	10.48***
	(20.50)	(10.20)	(5.972)	(8.060)	(12.69)	(3.145)	(2.541)	(2.555)
Weeks since first case FE		X		X		X		X
Weeks since first death FE			X	X			X	X
Observations	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189
R-squared	0.731	0.744	0.738	0.746	0.329	0.507	0.421	0.519
baseline mean	161.8	161.8	161.8	161.8	1.4	1.4	1.4	1.4
Panel B: Log changes								
post shelter in place	-0.797***	-0.521***	-0.546***	-0.432***	2.159***	0.976***	0.992***	0.691***
	(0.0248)	(0.0486)	(0.0235)	(0.0364)	(0.0831)	(0.116)	(0.0606)	(0.0834)
Weeks since first case FE		X		X		X		X
Weeks since first death FE			X	X			X	X
Observations	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189	2,739,189
R-squared	0.943	0.944	0.944	0.945	0.767	0.799	0.801	0.809

Caption: Baseline means are calculated based on the ninth week of 2019. Regression models were estimated using ordinary least squares. Regression models also include measures for the patient's age, gender, and county. Outcome measure is the number of patients, and all models are weighted for the total number of eligible enrollees. Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of Social Distancing Policies on Visits to Physician Office and Hospital Locations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Offices of Physicians				**Hospitals**		
Panel A: Level changes								
post shelter in place	-11.80***	-5.065***	-7.694***	-3.671***	-145.8***	-73.65***	-87.59***	-49.34***
	(0.352)	(1.043)	(0.666)	(0.834)	(11.75)	(14.68)	(10.50)	(14.95)
Weeks since first case FE		X		X		X		X
Weeks since first death FE			X	X			X	X
Observations	8,194,303	8,194,303	8,194,303	8,194,303	635,050	635,050	635,050	635,050
R-squared	0.030	0.030	0.030	0.031	0.318	0.319	0.319	0.320
baseline mean	45.5	45.5	45.5	45.5	490.1	490.1	490.1	490.1
Panel B: Log changes								
post shelter in place	-0.207***	-0.124***	-0.165***	-0.102***	-0.258***	-0.169***	-0.237***	-0.149***
	(0.00429)	(0.0155)	(0.00903)	(0.0114)	(0.0188)	(0.0200)	(0.0140)	(0.0182)
Weeks since first case FE		X		X		X		X
Weeks since first death FE			X	X			X	X
Observations	8,194,303	8,194,303	8,194,303	8,194,303	635,050	635,050	635,050	635,050
R-squared	0.056	0.057	0.057	0.057	0.428	0.430	0.429	0.431
Baseline mean	45.5	45.5	45.5	45.5	490.1	490.1	490.1	490.1

Caption: Unit of analysis is the number of visits in a week to an office of physician or hospital. Baseline means are calculated based on the ninth week of 2019. Regression models were estimated using ordinary least squares. Outcome measure is the number of visits. We use the four-digit NAICS code to identify office of physicians (6211) and general medical and surgical hospitals (6221). Standard errors are clustered at the county level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

8. APPENDIX

Table A1: Effect of Social Distancing Policies on Preventive, Elective, and Non-Elective Procedure Utilization—Differences by County Urbanicity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Preventive Care		**Colonoscopy**			**Mammogram**			**Immunizations**	
post shelter in place	-3.642***	-1.079***	-1.082***	-17.69***	-4.451***	-4.934***	-5.458***	0.765	-0.670
	(0.767)	(0.276)	(0.318)	(3.152)	(1.466)	(1.634)	(1.248)	(1.903)	(1.292)
Weeks since first case FE × urban		X			X			X	
Weeks since first death FE × metro type			X			X			X
Observations	818,153	816,870	816,870	406,616	405,964	405,964	320,303	319,698	319,698
R-squared	0.705	0.735	0.750	0.780	0.802	0.816	0.886	0.890	0.894
baseline mean	4.1	4.1	4.1	21.6	21.6	21.6	22.0	22.0	22.0
Panel B: Elective Care		**MRI**			**Musculoskeletal surgery**			**Cataract surgery**	
post shelter in place	-1.882***	-0.636***	-0.581***	-0.548***	-0.142**	-0.181**	-0.148***	-0.0560**	-0.0450***
	(0.390)	(0.158)	(0.156)	(0.124)	(0.0702)	(0.0722)	(0.0354)	(0.0235)	(0.0168)
Weeks since first case FE × urban		X			X			X	
Weeks since first death FE × metro type			X			X			X
Observations	2,739,189	2,734,831	2,734,831	2,739,189	2,734,831	2,734,831	2,739,189	2,734,831	2,734,831
R-squared	0.619	0.626	0.630	0.485	0.490	0.495	0.258	0.263	0.266
baseline mean	3.3	3.3	3.3	1.1	1.1	1.1	0.2	0.2	0.2
Panel C: Non-Elective Care		**Labor and delivery**			**Chemotherapy**			**Angiograms**	
post shelter in place	0.0600	-0.0520	0.0966	-0.0558**	-0.189***	-0.136***	-0.213***	-0.0634*	-0.0481
	(0.106)	(0.116)	(0.120)	(0.0276)	(0.0476)	(0.0389)	(0.0356)	(0.0374)	(0.0361)
Weeks since first case FE × urban		X			X			X	
Weeks since first death FE × metro type			X			X			X
Observations	818,342	817,035	817,035	2,739,189	2,734,831	2,734,831	2,739,189	2,734,831	2,734,831
R-squared	0.554	0.555	0.556	0.550	0.551	0.551	0.440	0.441	0.442
baseline mean	1.8	1.8	1.8	1.5	1.5	1.5	0.5	0.5	0.5

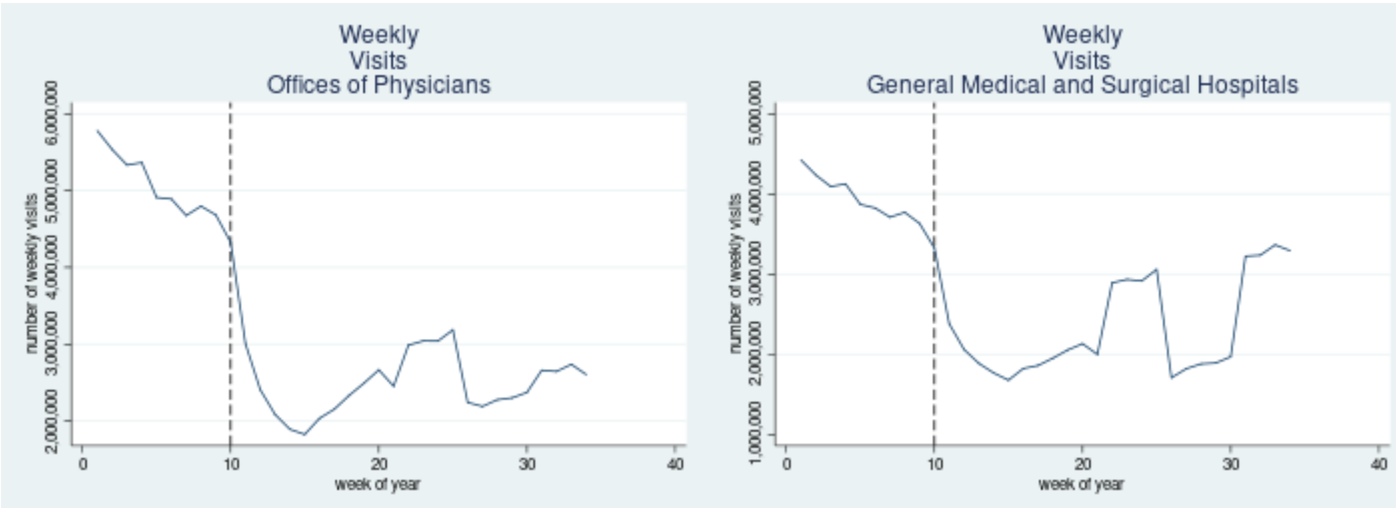
Caption: Baseline means are calculated based on the ninth week of 2019. Regression models were estimated using ordinary least squares. Regression models also include measures for the patient's age, gender, and county. Outcome measure is the number of patients, and all models are weighted for the total number of eligible enrollees. Standard errors are clustered at the county level. Immunizations are restricted to those aged 2 or younger. Colonoscopy is restricted to those 46 or older. Mammograms were restricted to females aged 46 or older. Deliveries were restricted to women between the ages of 19 and 45. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A2: Effect of Social Distancing Policies on Log-Transformed Preventive, Elective, and Non-Elective Procedure Utilization—Differences by County Urbanicity

	(1)	(2)	(3)	(5)	(6)	(7)	(9)	(10)	(11)
Panel A: Preventive Care		**Colonoscopy**			**Mammogram**			**Immunizations**	
post shelter in place	-0.745***	-0.286***	-0.263***	-1.002***	-0.528***	-0.441***	-0.156***	-0.119***	-0.125***
	(0.0703)	(0.0489)	(0.0638)	(0.0444)	(0.0608)	(0.0770)	(0.0158)	(0.0238)	(0.0246)
Weeks since first case FE × urban		X			X			X	
Weeks since first death FE × metro type			X			X			X
Observations	818,153	816,870	816,870	406,616	405,964	405,964	320,303	319,698	319,698
R-squared	0.748	0.768	0.780	0.879	0.892	0.898	0.930	0.931	0.931
baseline mean	4.1	4.1	4.1	21.6	21.6	21.6	22.0	22.0	22.0
Panel B: Elective Care		**MRI**			**Musculoskeletal surgery**			**Cataract surgery**	
post shelter in place	-0.296***	-0.139***	-0.123***	-0.176***	-0.0743***	-0.0803***	-0.0679***	-0.0243***	-0.0214***
	(0.0248)	(0.0213)	(0.0267)	(0.0238)	(0.0169)	(0.0225)	(0.0121)	(0.00818)	(0.00749)
Weeks since first case FE × urban		X			X			X	
Weeks since first death FE × metro type			X			X			X
Observations	2,739,189	2,734,831	2,734,831	2,739,189	2,734,831	2,734,831	2,739,189	2,734,831	2,734,831
R-squared	0.719	0.722	0.723	0.551	0.555	0.558	0.297	0.302	0.305
baseline mean	3.3	3.3	3.3	1.1	1.1	1.1	0.2	0.2	0.2
Panel C: Non-Elective Care		**Labor and delivery**			**Chemotherapy**			**Angiograms**	
post shelter in place	-0.00155	-0.0118	0.00135	-0.0173***	-0.0356***	-0.0294***	-0.0825***	-0.0416***	-0.0349***
	(0.00878)	(0.0142)	(0.0144)	(0.00507)	(0.0109)	(0.00927)	(0.0112)	(0.0120)	(0.0134)
Weeks since first case FE × urban		X			X			X	
Weeks since first death FE × metro type			X			X			X
Observations	818,342	818,342	818,342	2,739,189	2,734,831	2,734,831	2,739,189	2,734,831	2,734,831
R-squared	0.646	0.647	0.647	0.629	0.630	0.630	0.477	0.478	0.479
baseline mean	1.8	1.8	1.8	1.5	1.5	1.5	0.5	0.5	0.5

Caption: Baseline means are calculated based on the ninth week of 2019. Regression models were estimated using ordinary least squares. Regression models also include measures for the patient's age, gender, and county. Outcome measure is the number of patients, and all models are weighted for the total number of eligible enrollees. Standard errors are clustered at the county level. Immunizations are restricted to those aged 2 or younger. Colonoscopy is restricted to those 46 or older. Mammograms were restricted to females aged 46 or older. Deliveries were restricted to women between the ages of 19 and 45. *** p<0.01, ** p<0.05, * p<0.1

Appendix Figure 1: Trends in Weekly Visits to Physician Office and Hospital Locations Using Cellular Phone Mobility Data for 2020



Caption: Total number of weekly visits were calculated for hospitals and offices of physicians in the SafeGraph data. We use the four-digit NAICS code to identify office of physicians (6211) and general medical and surgical hospitals (6221).