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EFFECTS OF STATE COVID-19 CLOSURE POLICY ON NON-COVID-19 HEALTH CARE UTILIZATION

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ABSTRACT

The U.S. health care system has experienced great pressure since early March 2020 as it pivoted to providing necessary care for COVID-19 patients. But there are signs that non-COVID-19 care use declined during this time period. We examine near real time data from a nationwide electronic healthcare records system that covers over 35 million patients to provide new evidence of how non-COVID-19 acute care and preventive/primary care have been affected during the epidemic.

Using event study and difference-in-difference models we find that state closure policies (stay-at-home or non-essential business closures) are associated with large declines in ambulatory visits, with effects differing by type of care. State closure policies reduced overall outpatient visits by about 15-16 percent within two weeks. Outpatient visits for health check-ups and well care experience very large declines during the epidemic, with substantial effects from state closure policies. In contrast, mental health outpatient visits declined less than other care, and appear less affected by state closure policies. We find substitution to telehealth modalities may have played an important role in mitigating the decline in mental health care utilization.

Aggregate trends in outpatient visits show a 40% decline after the first week of March 2020, only a portion of which is attributed to state policy. A rebound starts around mid April that does not appear to be explained by state reopening policy. Despite this rebound, care visits still remain below the pre-epidemic levels in most cases.

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1 Introduction

Since the start of the COVID-19 epidemic, state and local governments have adopted a range of policies that are designed to reduce the transmission of the virus (Gupta et al., 2020a). These policies are part of an effort to reduce the number of people who are infected with the virus at any given time. Flattening the epidemic curve in this way makes it less likely that the epidemic will overwhelm the capacity of local health systems. In addition to social distancing policies – such as non-essential business closures, school closures, and stay-at-home mandates – many states and hospitals have also acted to restrict or delay the use of healthcare resources for elective, non-essential, and non-urgent purposes. These policies were intended to conserve personal protective equipment, free up physical space in healthcare facilities, and ensure that healthcare workers had the capacity to treat COVID-19 patients safely (Sarac et al., 2020). A recent review of the literature shows that the epidemic has led to a large reduction in measures of physical mobility, consumer expenditures, and labor market activity (Gupta et al., 2020b).

Although state and local public policies have played an important role, they occurred after large declines in mobility in most states. This suggests that much of the decline in mobility and economic activity is rooted in private decisions that people have made in order to reduce the risk that they will contract the virus or transmit it to someone else (Goolsbee and Syverson, 2020; Cronin and Evans, 2020; Gupta et al., 2020b). The combination of private responses and public policies related to the epidemic likely affected the way people use the health care system for health conditions that are not related to COVID-19. Early reports show large declines in emergency department visits (Hartnett, 2020), elective procedures, and primary care utilization (Mehrotra et al., 2020). In some cases, patients may be deferring care that they will eventually seek in the future. In other cases, people may have foregone care entirely and will not catch up on the lost services. Both deferred care and foregone care may have important implications for a person's current and future health.

In this paper, we study the effects of state policies and private responses to the epidemic on health care utilization for non-COVID-19 health conditions. We examine changes in health care utilization during the shutdown phase of the epidemic and in the early part of the reopening phase of the epidemic, when healthcare utilization rebounded substantially. Our work sheds light not only on the overall decline and recovery of healthcare utilization, but also on the ways that the epidemic has disrupted some types of services and therapies more than others. Understanding these patterns may be important for efforts to manage a possible second wave of the epidemic. To the extent possible, we seek to identify types of care that most affected by policy changes and epidemiological conditions. We also examine the extent to which substitution between live and remote (telemedicine) helped maintain the delivery of health services in some domains.

Finally, our work also contributes to research on the marginal benefit of additional medical care. This work seeks to disentangle patient selection into care from the benefit of the care itself, usually with the goal of determining whether certain types of care reflect wasteful "flat of the curve" spending. Previous work on this topic finds mixed evidence, with some studies showing large benefits of additional medical spending (e.g. Doyle (2011); Doyle et al. (2015)) and other papers showing limited or no benefit associated with additional spending (e.g. Fisher et al. (2003)a,b; Frakes (2013)). Building on our results here, we will be able to identify the health returns to medical spending in a novel environment where certain types of services were rationed, delayed, or cancelled.

2 Related Research

2.1 Types of Care Delayed During COVID19–Existing Literature

Although traditional sources of health care use such as nationally representative surveys or administrative sources (HCUP) are available with a lag of two years or more, there are a number of data sources that demonstrate large declines in nonCOVD19 related care.

One source that has been used in the prior literature is the National Syndromic Surveillance Program (NSSP), a partnership between CDC, other federal units, local and state health departments and academic and private sector partners that draw on electronic patient encounter data, drawing from emergency departments, urgent and ambulatory care centers, inpatient healthcare settings, and laboratories. NSSP is connected to Public Health Security and Bioterrorism Preparedness and Response Act of 2002, Pub. L. No. 107-188. (https://www.cdc.gov/nssp/index.html). Coverage is broad, including 73% of emergency department visits as of April 2020, covers 47 states (all but Hawaii, South Dakota, and Wyoming), and data are available 24 hours after a patient visit.[1]

Hartnett (2020) uses data from NSSP for comparable periods during 2019 and 2020 to show large declines in all ED visits. Specifically, a reduction of 42% (1.2 million per week nationally in March 29–April 25, 2020 compare to 2.1 million per week during March 31–April 27, 2019).Reductions were pronounced for those aged younger that 14 years, females, and

[1]This source is not without limitations. For example, close to 300 new hospitals were added to the system between 2019 and 2020 and 20% of cases were missing diagnostic codes

the Northeast region.

There has been a fall in the number of patients with heart attacks who are visiting Emergency Departments, that has been widely noted (eg: Krumholz (2020) and Sheth (2020)).

Bhatt et al. (2020) uses data from Jan 1 2019 to March 31 2020 from Mass General Brigham health system to show that daily acute cardiovascular hospitalization reduced on average 43.4% in March 2020 compared to March 2019. There was also a shorter length of stay, but no statistically significant difference in in-hospital mortality. Declines in acute coronary syndrome hospitalizations has also been found in Italy, in De Filippo et al. (2020)

A study using electronic health records from Epic (Trinkl and Sizemore, May 14th) showed declines in cardiac related hospital admissions using electronics health records covering 22 health systems in 17 states, and including 7 million patients. The data period spanned April 2, 2019 – April 7, 2020, and showed that weekly acute myocardial infarctions (AMI) admissions to the ED dropped by 45% after March 13 2020 and that weekly admissions for strokes decreased by 38%. [2]. The number of visits began decreasing in the few weeks before March 13th. An update posted July 7th using the same data shows that in the 9 weeks since April 7th 2020, there is a return to "near normal" visit rates (92% and 87% of the pre March 13th levels) for these two conditions.

Also related to cardiac care, Garcia et al. (2020) documents that there was a 38% reduction in primary percutaneous coronary intervention (PPCI) for ST-segment elevation myocardial infarction (STEMI) patients at 9 high-volume US cardiac catheterization labs from March 1-March 31 2020 compared to January 1, 2019 to February 28th, 2020.

There is a smaller literature on the changes in non-hospital care. Research using electronic health records from Epic shown a decline in cancer screenings, this time using data from 60 healthcare organizations, that draw from 306 hospitals in 28 states, representing 9.8 million patients. In this study, the pre-period is 2017 through January 19, 2020. Mast and Munoz del Rio (2020) show that the number of preventive cancer screenings in the data dropped 86% for colon cancer and 94% for breast and cervical cancer. Unlike for AMI and stroke ED admissions, by June 16th, there was not as much of a catch-up to historical rates for these cancer screenings. Even in this last week of the data, the weekly number of visits was 29%, 36%, and 35% lower than pre March 13th weekly levels for breast, colon, and cervical cancer screenings. Beyond screenings, there is (anecdotal) concern that maintenance therapy was also postponed Rosenbaum (2020).

There is not much known yet on elective procedures. A study looked at state guidelines on what defines elective care, as of March 24th 2020 Sarac et al. (2020). They found

[2] Stroke admissions also noted in a news article Sheth (2020)

that 30 states had provided guidelines to hospitals, but only 16 states defined what constituted elective procedures and only 10 states provided guidelines for continuing oncological procedures.

In the closest research to date, Mehrotra et al. (2020) show in a series of reports the changing trends in outpatient care. They use data from a healthcare IT organization Phreesia, which tracks 50,000 providers. They report in April ambulatory care practice visits reduced almost 60 percent. In May, visits still remain about 1/3rd lower compared to pre-COVD19 shutdowns. The rebound was largest in the Southcentral census region of the US.In-person visits declined the most, and were a larger part of the rebound. Between 3/8/20 and 4/19/20 there was a rapid increase in telehealth visits, but it has plateaued and decreased since then, as a share of all outpatient visits. The largest declines were in surgical and procedural specialties (79% drop in opthomology, 62% drop in orthopedics, as of the week starting April 30th 2020) and the smallest was in behavioral health (30%). The decline in visits was larger among younger patients and the rebound also smaller among younger patients.

2.2 Effect of state closure policies on economic activity

There is no work as yet examining the effect of policy on these health care declines, but a large literature comments on the effect of state policies on other economic activities, including consumer spending, human mobility and labor markets. There is also a literature related to health care delivery remotely that is relevant for our research.

2.3 Telehealth

Verma (2020) documents that from March 17th to April 26th 2020, there was a dramatic rise in Medicare telehealth visits even in preliminary data. The rise was from 0 to almost 1.8 million FFS medicare telemedicine visits per week. CMS reports that telemed visits in Medicare, which became reimbursable after the March 13th federal emergency declaration allowed waivers of Medicare program requirements, allowed all visits to occur and be billed by telehealth in any location.[3] Due to public health emergency, many barriers were lifted in Medicaid as well. These changes allowed, for example, that patients and providers do not have to meet in person before telehealth, can do audio-only meeting, same billing as in-person visit. This poses an issue also for how telehealth is tracked as an outcome in our

[3] see declaration here: https://www.cms.gov/newsroom/press-releases/emergency-declaration-press-call-remarks-cms-administrator-seema-verma

data. We discuss this in our data section in detail but note here that we are able to examine all outpatient visits whether in−person or telehealth.

2.4 Consequences of delayed medical care

A literature in medicine documents the consequences of delayed medical care. Weissman et al. (1991). While this literature examines institutional factors that affect delaysBrunner et al. (2020), and this question is related to research from health insurance expansions that work in the opposite direction (increasing access to health care and reducing delays), to the best of our knowledge there has not been literature that comments on the causal impacts from exogenous delays. Thus, this research represents an important opportunity to advance the literature on identifying high-value care and the health consequences of exogenous delays for different types of health care.

3 Data

3.1 Healthjump

There are as yet few sources of comprehensive health care data covering the last few months. Electronic health care records are available much sooner (often with a day of the encounter) than other health care data sources such as those from claims or surveys. However, there are difficulties faced in assessing representativeness of existing electronic health records databases(Montvida et al., 2020).[4]

For our study, we obtained medical care utilization data from January 1 2019 to June 2020 from an electronic health records database available through the COVID19 Research Database. This Database is a pro-bono, cross-industry initiative, composed of institutions donating de−identified data for COVID19 research.[5]

The specific database we use is from Healthjump, a data management platform that solves interoperability challenges facing digital health vendors needing access to electronic medical records (EMR). As an example, Healthjump receives data from various healthcare organizations that already use EMR vendors such as Cerner, Epic, NextGen and would like to standardize their records across various platforms. Healthjump extracts the EMR data,

[4] For a review of electronic health records research, see Atasoy et al. (2019)

[5] We obtained access through submitting a research proposal to the COVID-19 Research Database Scientific Steering Committee. More details on accessing these data are available at https://covid19researchdatabase.org/. Also see the use of these data for COVID19 research: Akbarpour et al. (2020).

standardizes it and remits it back to the healthcare organization continuously (overnight). The Healthjump website provides a list of all EMR vendor integrations from which their system pulling records [6]. The data being extracted from these EMR vendors includes demographics, appointments, encounters, charges, transactions, medical history, medications, diagnosis, procedures, allergies, immunizations, labs, provider, social history and vitals.[7]

The advantage of these data is that they contain rapidly accessible EMR for a large portion of the US population, including all patients of the covered health care organizations, regardless of payer type.

The database sample we use contains data on approximately 35 million unique patients and spans January 2019 to June 2020. Below, we describe the structure of this dataset and the characteristics of the patients it represents.

The Healthjump EMR sample we use contains information from ambulatory care providers, which include outpatient physicians, urgent care and emergency room visits.[8] In our current analysis, we focus on outpatient visits, procedures and laboratory tests. For a given visit, recorded items include the appointment reason (ICD9/10), duration in minutes, any outpatient procedures performed (HCPCS/CPT codes), any laboratory tests ordered (CPT or LOINC codes), the results of these laboratory tests, and the patients vitals at the appointment time. A demographic file includes the patient's date of birth, race, sex, ethnicity, state and the 3 digit zip code of residence and a unique patient identifier that is linkable to other files. We did not receive access to the charges file; charge information is usually preliminary in EMR because they do not necessarily correspond to eventual charges in the submitted claim.

As stated above, we focus on outpatient visits, outpatient procedures and laboratory tests, all specifically for non−covid19 care. This leads us to a sample size of 28,157,247 outpatient visits in the database between Jan 2019 and June 2020. These visits are provided by approximately 13,000 unique providers.[9]

[6] see https://www.healthjump.com/integrations

[7] The data are certified as de-identified and already collected, thus this research was deemed non-human subjects research by Indiana University's Human Subjects Office.

[8] Although inpatient data exists, it "typically comes by way of the ambulatory EHR systems within an (*integrated delivery network)* IDN".

[9] We initially recorded 15,000 unique providers but we decided to remove any EMR vendors or providers that were not in the data in both 2019 and 2020. This eases our ability to compare outcomes across years. But reduced our sample by 700,000 observations (2.4%) before arriving at our total of 28,157,247 outpatient visits. It is worth comparing our ratio of providers to outpatient visits with the data from Mehrotra et al. (2020), an earlier report on electronic health records, which included approximately 1 million visits per week and a total of 50,000 providers. In our full sample, there are approximately 375,000 visits per week and 15,000 unique providers. This leads to 20 and 25 as the average number of patient visits per provider.

For each individual visit, we are able to track all of the medical procedures executed and laboratory exams ordered for the event of care. A unique feature of this data is that we are able to distinguish between an appointment booked and an appointment attended, an especially valuable feature when studying the early period of the closures. Throughout this study, we examine only appointments actually attended.

We keep track of the frequency of all visits, and visits that make up a large share of outpatient services or are for chronic care. To characterize the diagnoses codes into groups of visits we use the 9th and 10th revision of the International Statistical Classification of Disease and Related Health Problems Chapters to create six groups of visits. The types of care we examine are the following : 1. circulatory disease visits (ICD10 code Ixx, OR ICD 9 code 390-459) which includes encounters for hypertensive disease, heart failure and cerebrovascular diseases 2. Endorcrine disease visits (ICD 10 EXX or ICD 9 240-279) which include diabetes mellitus. 3. Musculoskeletal disease visits (ICD 10 MXX or ICD 9 710-739) which include Rheumatism and all Arthropathies. 4. Neoplasm disease visits (ICD 10 C00-D48 or ICD 9 140-239) which include malignant, benign, in situ and tumors of unknown behavior. 5. Mental and Behavioral Health Visits (ICD 10 FXX or ICD 9 290-319) which include visits for all mental disorders and mental health disorders due to substance abuse. 6. Health Status and visits for contact with health services (ICD 10 ZXX or ICD 9 Vxx). This final category, includes approximately 25% of all outpatient visits and is defined by the ICD9/10 chapters to include services such as follow−up visits post surgery, immunization, annual health checkups and prenatal care. One advantage of creating these broad categories is that we can examine several thousand ICD codes easily and without running into an issue of multiple hypothesis testing. However, when we examine outpatient procedures we report more granular types of care such as chemotherapy, cancer screening and cardiac stress testing. Finally, from the CPT codes associated with the visit, we are able to identify (although with limitations) whether the encounter was a Telehealth or face to face visit. We discuss this in detail later on.

We investigates the relative size of our data set, and found it contain approximately 13% of the US. AHRQ (2020) reports that 85.4% of the US reports having a health expense at some point during the year [10]. Multiplying this by the US population of 321,423,000 in 2015 in that source implies there would be 274,495,242 people receiving care in a typical year. Since our data source shows 35,143,966 unique patients in our study data (when limited to our consistent panel), that constitutes approximately 13% of the US population that seeks care.

[10] Agency for Healthcare Research and Quality. Number of people in thousands, United States, 2015-2017.

We start by showing characteristics of those who are registered in the Healthjump database. Table 1 contains summary statistics of the sample. There are two important things to note about Table 1. First, the average age of registered patients is 53.76 which reflects that our sample includes both the elderly and the non−elderly (under age 65). Second,a significant portion of the sample is missing a race entry. Approximately 70% of registered patients have a missing race entry and 58% if registered patients have a missing ethnicity entry. The share missing both race and ethnicity is approximately 57%. We note that when we examine patients who have actually had visits (28 million sample), the share missing both race and ethnicity decreases significantly to 21.7%, which indicates that race and ethnicity information is being entered at the time of the visit (even if also collected from elsewhere). However, this large degree of missing data on race and ethnicity mean that we will be unable to examine disparities in health care outcomes.

Below we discuss some comparisons between our patient population and those in the National Ambulatory Medical Care Survey (NAMCS) which collects data on the utilization and provision of ambulatory care services from a nationally representative sample across the US.[11][12] In Table 2, we compare those in our sample who had visits in 2019 (our baseline year) to those with visits during the year 2016 in the NAMCS (latest available, using person weights). The fraction female is 58% in the Healthjump data and a very close 57% in NAMCS. In terms of race and ethnicity, the share non−Hispanic white is 83% in our sample and 82% in the NAMCS. Our sample slightly over represented in some ways: non−Hispanic black (15% in Healthjump vs 11% in NAMCS) and slightly under represents in other ways (12% Hispanic in Healthjump vs 17% in NAMCS).[13] There is a greater difference in age–the average is 45.1 nationally in NAMCS and 52.8 in our sample, so more than a 5 year average difference. This is the first illustration of how Healthjump is not a nationally representative data base. The next rows show that the age difference between this sample and national visit data is particularly driven by a lack of younger patients in our data set (only 10% of the sample here but 21% of national visit data). [14]

[11] Collected by the National Center for Health Statistics, CDC (www.cdc.gov/nchs/ahcd/index.htm)

[12] NAMCS is a longstanding survey of visits to a sample of nonfederal office-based physicians as well as visits to community health centers.

[13] To allow for comparison, we calculate the share of patients who are non−Hispanic white, non−Hispanic black, other race and Hispanic from the total population of patients with non−missing race/ethnicity entries in both Healthjump and NAMCS.

[14] To explore this issue later we investigate whether there are systematic differences in which providers have adopted EMRs. Based on the National Electronic Health Records Survey, NEHRS, another NCHS annual survey, latest data available for 2017 shows that 85.9% of physicians are part of any EHR or EMR system. It is likely that this number is higher in 2020, but one reason that the Healthjump data are not nationally representative is that not all office-based care is captured in electronic health records

As there is also the concern that the composition of patients may differ during the pandemic, we show sample characteristics separately by quarter in Table 3. As seen elsewhere in Mehrotra et al. (2020), there has been a reduction of visits among both older and younger patients, and the rebound has not been as great for the younger group. The younger group may be seen less often particularly because of the protective role of parents and because their conditions maybe more postponable, whereas the oldest group may reduce visits particularly because of consequences of COVID19 being higher for them (Williamson et al. (2020)) but rebound faster as their conditions are less postponable. Consistent with those observations, we see an increase in average age from 53.15 to 54.73 between Q2 2019 and Q2 2020, which suggests bigger reductions in care among younger patients. The share of patients who are under 18 in Q2 goes from 0.087 in 2019 to 0.062 in 2020. The share of patients who are 65+ remain about the same; corresponding numbers are 0.353 and 0.368, while the share 18-64 rises from 0.539 to 0.548. Similarly, and also indicative of some selection, the share of White non−Hispanic patients decreases from 0.823 to 0.814 and non−Hispanic Black increases from 0.156 to 0.168. The increase in the share of non−Hispanic black is suggestive of increases in the share of comorbid patients receiving care.[15]. We note that it is not possible to know whether this reflects a real change or just an improvement in reporting of race and ethnicity over time, but we also note that there does not seem to be a steady improvement rate in reporting of race, that this seems unique to q2.

Next, we explore the representativeness of the data by state. These data are not selected as a sample to be nationally representative, and we will be cautious in interpreting the results this way. Our empirical models will contain state fixed effects, which should control for time-invariant charactertistics that would confound estimates.

Table 4 shows the distribution of visits, and of the demographic composition, by state. The columns 'Female' through 'Hispanic among non-missing' show fractions of the state's visit population that fit into these categories. The fraction female is fairly close to .60, with some exceptions (37% in Iowa and 73% in MO). The age ranges display some variation across states, ranging from the 40s to the 60s. There is variability in the categories of ages used too, although in almost all states, the share 18-64 years of age is about a half or more or the visits. The racial and ethnic composition varies across states. The last 5 columns of 4 give a

https://www.cdc.gov/nchs/data/nehrs/2017_NEHRS_Web_Table_EHR_Specialty.pdf. However, as we will point out in later tables, there are also likely differences in geographical coverage that make the data not nationally representative.

[15]The rate of comorbidity is generally higher among non−Hispanic black relative to non−Hispanic white. For example, a longitudinal study of participants in the 2000 Health and Retirement Survey, found that middle-aged non-Hispanic black develop multimorbidity at an earlier age, on average, than their non-Hispanic white counterparts (Quiñones et al. 2019)

sense of whether some states are over or under represented in the data. The number of visits by state is listed, then the state's population (as of July 2019 from the Census Bureau). We then show the share of the US population that lives in that state, and the share that state comprises of the visits. The last column calculates the share of visits divided by the share of population, for a state. States that have a value of 1 are represented in exact proportion to the population distribution. This allows us to see that some states like Delaware, Utah, Mississippi are represented five to six times as much as their population distribution, while other states like Wisconsin, Tennessee and New Hampshire are represented very little relative to population.

An important take-away from examining these data are that they should not be taken as a nationally representative sample, but we provide details above so readers can assess which states are represented in the sample and their patients' characteristics. In all analyses moving forward, we limit our sample to 31 states at least 100,000 visits between 2019 and 2020.

3.2 Distinguishing Telehealth from Face−to−Face Visits

When we examine outpatient visits and outpatient visits by reason we examine the total visits regardless of location (telehealth or physician office). This is because it appears both encounters are likely recorded as regular visits, even if performed as telehealth.

To aid the uptake of telehealth, CMS created new HCPCS service codes. These consist of a list newly created specifically for telehealth services, as well as 238 existing service codes, which now could be billed via telehealth.[16]. This list of existing codes that could be used when billing for telehealth services, include the service codes 99202-99205 for new patient outpatient visit and 99211-99217 for existing patient outpatient visits. In the pre−pandemic period, these few codes alone were regularly used by physicians.

In our data, we found 83,000 visits with telehealth specific codes (majority appearing between March 2020 and May 2020) and approximately 2.9 million visits with telehealth eligible codes. The latter means, a visit that may or may not be telehealth but was designated by CMS as telehealth eligible in the pandemic period.

Given that a mix of existing and new service codes are being used, it is impossible to perfectly untangle what services were and were not telehealth visits without information on the location of the visit. To over come this issue and still examine the effect of state policy on telehealth services we define two broad categories of services as those that allow

[16]See full list here: www.cms.gov/Medicare/Medicare-General-Information/Telehealth/Telehealth-Codes

for telehealth and those that do not allow for telehealth. We understand that we are unable to tell which of the visits of the codes that can be used for either, were actually provided face to face vs remotely, but we do know that those in the excluded category (all else) could only be reimbursed if used for a face to face visit.

We next move on to describing how we characterized the state COVID-19 policies relevant for this study, those are policies that guide human mobilty as well as the specific health care elective procedures rules.

3.3 State Policy Data

Many states have responded to the COVID-19 pandemic by enacting a variety of laws and policies related to limiting the spread of the associated virus and ensuring that healthcare resources are freed to absorb COVID-19 patients. To characterize state policies, we reviewed the range of policies and dates of implementation used in prior studies (see Gupta et al. (2020a) for a detailed topology of state and local actions used in the COVID-19 social distancing and mobility literature). Our goal was to accurately identify the implementation date of a policy and to classify in a parsimonious way main elements of a state's policy response, particularly, those that could potentially affect healthcare utilization during the pandemic.

Based on our review, we chose five policy measures: Two policies relating to state closures and reopenings, two policies related to suspending and resuming "non-urgent or elective" medical procedures and whether the state passed directives that provide immunity from civil liability to physicians.

The most prominent state response has been the enactment of state closures. These policies take the form of either stay at home orders or non-essential business closures or both. We use the dates on state closure policies that were previously reported in Gupta et al. (2020a). There the authors report both the date of the stay at home orders and the non-essential business closure. Almost all states enacted stay at home orders and of those a large majority enacted the stay at home orders on the same day as the non-essential business closure (see Appendix Table A.1). We therefore, define state closure to be the earlier date of either the stay at home order or the non-essential business closure. The next policy category identifies the date the stay at home order was removed or non-essential businesses began reopening (phase I). Again we define this date to be the earlier of the two.

States have also taken steps to reduce the utilization of "non-urgent or elective" medical procedures. Below we discuss the topology of these policies and where future research may be needed in classifying the type and intensity of these state orders.

On March 18, 2020, the CMS released recommendations concerning the delay of elective procedures [17]. These recommendations outlined factors that should be considered for postponing elective surgeries and non-essential medical, surgical, dental procedures, including reference to patient risk factors, availability of beds, staff, PPE and the urgency of the procedure. The CMS guideline stated that the "decision about proceeding with non-essential surgeries and procedures will be made at the local level by the clinician, patient, hospital, and state and local health departments". Thus, at the federal level there was only guidelines and no directives or orders,

At the state level, there was much activity in this area. We scanned the state orders and directives and identified the date that non-urgent or elective services were ordered to suspend, if at all. In total thirty-six states ordered the discontinuation of elective and non-urgent procedures. See Appendix Table A.1 for the list of states and dates.

States varied significantly on the amount of guidance they provided for distinguishing between services that should be delayed and those that should not. A large share of state laws and directives specifically referenced the CMS surgical guidelines (but did not require hospitals and physicians to adhere to it). This guideline is a tiered approach for surgical services [18]. Tiers 1, 2, and 3 designate low, intermediate, and high-acuity procedures, respectively, whereas the designations "a" and "b" indicate healthy and unhealthy patients. CMS recommends postponing all Tier-1 operations, to consider postponing Tier-2 operations, and to continue performing Tier-3 operations. All Tier-1 operations were procedures that belonged in hospital outpatient departments and ambulatory surgical centers. Since our emphasis here is on outpatient and ambulatory care, a majority of the surgical procedures that appear in our data are under this Tier 1 classification. Therefore were did not need to identify patients likely or unlikely to have medical procedures deferred. Nonetheless, we provided this description to shed light on this definition that maybe useful to researchers specially when examining (Tier 2 and Tier 3) inpatient services.

Aside from recommending that physicians review the CMS guidelines, three states added specific definitions for what constitutes "non-urgent or elective" care that is based on time. North Carolina defined this care to be "any procedure or surgery that if not done within the next 4 weeks would cause harm to the patient". Colorado and New Mexico, defined it as care that "can be delayed for a minimum of three months without undue risk to the current

[17] https://www.cms.gov/newsroom/press-releases/cms-releases-recommendations-adult-elective-surgeries-non-essential-medical-surgical-and-dental

[18] https://www.cms.gov/files/document/cms-non-emergent-elective-medical-recommendations.pdf

or future health of the patient". Still, the probability of a complication within a specific time frame is a decision mainly within the physician's discretion and is not a standardized rule.

Overall, based on our reading of these state orders, a recurring theme is that the terms "non-urgent or elective" were not fully defined and the states mainly recommended that hospitals create a physician task force that would be available to evaluate on a case-by-case basis and make a determination on borderline cases[19]. Hence, for now, we opted to only use the variation from the date that states ordered elective or non-urgent procedures to suspend and the date these procedures were allowed to resume.

Since postponing elective procedures potentially raises liability concerns. Some states have have taken additional steps to provide protection to physicians who have shifted their practices to telemedicine and those whose treatment decisions may have been based on government directives. Earlier research has pointed to the impacts of medical malpractice pressures on physician treatment decisions (Frakes and Gruber (2019) and Mello et al. (2020)). It is therefore plausible that states that added these liability waivers may have higher rates of physician compliance with the directives related to the postponement of elective and non-urgent care. Below we describe the nature and language used in this legislation and how we characterize these liability waiver policies in our model. No prior research has shed light on these waivers and so we proceed with many details.

In total, sixteen states expanded civil liability protections for health care providers that could arise due to deferred or rescheduled care. Those states are Alabama, Arizona, Arkansas, Connecticut, Georgia, Illinois, Kentucky, Louisiana, Mississippi, New Jersey, New York, Oklahoma, Utah, Vermont, Virginia, and Wisconsin). To obtain the list of these states, we carefully read through state order and legislation enacted during the pandemic and reported on billtrack50.com, legiscan.com, the American Medical Association (AMA) and the National Conference of State Legislature (NCSL).

The language of these civil liability waivers varied slightly across the 16 states. All 16 states, except Oklahoma, extended liability protection both to providers who treated COVID-19 patients and those who did not. Oklahoma, only extended liability protection for "an act or omission in the provision of health care services to a person who did not have a suspected or confirmed diagnosis of COVID-19 at the time of the services." Four states made direct reference to protection for liability concerning damages from delay of elective procedures (Arkansas, Louisiana, Vermont and Wisconsin). Fourteen states (Alabama, Arizona,

[19]See also a review of the state policies on elective medical procedures by the AMA https://www.ama-assn.org/system/files/2020-06/state-elective-procedure-chart.pdf

Arkansas, Connecticut, Illinois, Mississippi, New Jersey, New York, Ohio, Oklahoma, Utah, Virginia, Kentucky and Wisconsin) offered liability protection for any “acts or omissions” of a medical professional in the course of providing care, as long as the provider was acting in good faith.[20] Two states (Georgia and Louisiana) had passed laws or included a section in their state code before the pandemic that expanded provider liability protection in the event of the state declaring a public health emergency. Only one state, Alabama, limited the damages that could be paid out if a provider were to be found liable for an act of “wanton, reckless, willful, or intentional misconduct.” In these cases, liability is “limited to actual economic compensatory damages,” barring any “non-economic or punitive damages.”

To decide the start date of the liability waivers, we chose the date the bill was enacted or the date of the emergency declaration; if the bill retrospectively assigned medical liability waivers for care provided since the emergency declaration.

Figure 1 shows changes over time in the state policies between March 1st 2020 and May 31st 2020, using the five policies classification discussed above (state closure, state reopening, elective medical procedures suspended, elective medical procedures resume, and the state medical liability waivers). As Figure 1 shows, there is variation over time within states in both the extensive margin reflected in the share of states that closed and that ordered the postponement of elective procedures, and at the intensive margin, reflected in the share of states that added liability waivers when ordering physicians to delay elective care.

4 Methods

To shed light on the way that the COVID-19 epidemic has affect health care utilization in the U.S. we combine the HealthJump EMR data with data on the timing of state policies and estimate event study and generalized difference in difference regression models. The unit of analysis in all of our models is the state-week. The outcome variables are measures of the total number of specific types of outpatient visits, procedures, or laboratory tests that are captured in the EMR data in each state-week.

4.1 Event Study

Use $s = 1...31$ to index the states in our sample, and let $t = 1...66$ index the weekly time periods. In all of our regressions there are $31 \times 66 = 2046$ state-week observations. Let C_s be the week that state s imposes a closure policy, and let E_s be the week that the state suspends

[20]Kentucky did not directly use this phrase but used the similar terminology “act or failure to act.”

the provision of elective medical procedures.[21] Next, let $TSC_{st} = t - C_s$ and $TSE_s st = t - E_s$ measures the number of weeks between week t and the closure and elective medical procedure policies, respectively. We set $TSC_{st} = 0$ and $TSE_{st} = 0$ for states that never experience the events, and we fit event study regression models with the following structure:

$$
\begin{aligned}
y_{st} = & \sum_{a=-8}^{2} \alpha_a 1(TSC_{st} = -a) + \sum_{b=0}^{6} \beta_b 1(TSC_{st} = b) \\
& + \sum_{a=-8}^{2} \delta_a 1(TSE_{st} = -a) + \sum_{b=0}^{6} \lambda_b 1(TSE_{st} = b) \\
& + \theta_s + \gamma_t + \epsilon_{st}
\end{aligned}
$$

In the model, θ_s is a set of state fixed effects, which are meant to capture fixed differences in the level of outcomes across states that are stable over the study period. γ_t is a set of week fixed effects, which capture trends in the outcome that are common across all states. ϵ_{st} is a residual error term. α_a and β_b are event study coefficients that trace out deviations from the common trends that states experience in the weeks leading up to and following the closure policies. Specifically, α_a traces out differential pre-event trends in the outcome that are associated with states that go on to adopt the closure policy. β_b traces out differential post-event trends in the outcome that occur after a state imposes the closure policy. δ_a and λ_b are the event study coefficients associated with the elective procedure policies. The reference period in all event studies is the period before adoption, when $TSC_{st} = -1$ and $TSE_{st} = -1$. We estimate the model using a Poisson fixed effect regression, which is reasonable because the outcome variable is the weekly count of various types of outpatient visits. However, we relax assumptions about the Poisson error term by estimating standard errors using a cluster robust variance matrix that allows for heteroskedasticity and for clustering at the state level.

Our event study specifications are based on a balanced panel of 31 states, that have at least 100,000 visits during our sample period, observed for 66 weeks.[22]In principle, the length of the event time "window" could be very long. However, the coefficients that are far from the onset of the event would be identified by only few states that adopted the policy very early or very late. To avoid bias from composition change from one event study coefficient to the next, we set the length of the focal event time window to run from 8 weeks before the event and 6 weeks after the event, which keeps compositional variation low. In practice, this

[21] We define the closure data as the earlier of the date that the state closed non-essential business, and the date the state imposed a stay-at-home mandate.

[22] Since we start our regression analysis panel in January 2019 and end in mid May 2019 and exclude all weeks with national holidays we have a panel of 66 weeks.

means we set $TSC_{st} = 6$ if $t - E_s \geq 6$ and $TSC_{st} = -8$ if $t - E_s \leq -8$ to "dummy out" the event study coefficients outside the focal range. We use the same approach for the elective medical procedure policies. The event study graphs we present only show the coefficients in the focal range 8 weeks before and 6 weeks after.

4.2 Generalized Difference in Difference

The event study models provide a flexible platform for analyzing the effects of state policies on health care utilization during the early part of the epidemic. However, it is somewhat cumbersome to estimate these models for a broader collection of policies. And the event study functional form may be statistically imprecise, especially if it is plausible to assume that there really are no pretrends and the effects of the policy are approximately constant over the six week post-policy period. Under these additional assumptions, we examine generalized difference in difference regressions with the following form:

$$\begin{aligned} Y_{st} = \beta_0 &+ \beta_1 StateClosure_{st} + \beta_2 ElectiveSuspended_{st} \\ &+ \beta_3 StateReopen_{st} + \beta_4 ElectiveResume_{st} + \beta_5 LiabilityWaiversst + \delta_s + \tau_t + \epsilon_{st} \end{aligned}$$

In this specification, δ_s is a state fixed effect, τ_t is a week fixed effects, and ϵ_{st} is a residual error term. The mdoel also includes five indicators for whether the state has ordered a closure, suspended elective procedures, reopened, resumed elective procedures and added medical liability waivers. We define each policy variable as the proportion of the previous calendar week that the policy was in effect. In the results, we present estimates from models that only include the closure policies, and models that use all policies at once. We also fit models that allow for state-specific linear year trends to the model, which may help account for possible changes in the composition of the HealthJump EMR data over time. (The results are not sensitive to the inclusion of the state specific trends.) As with the event study analysis, we fit Poisson fixed effect models and compute standard errors using a cluster robust variance matrix.

5 Results

We examine the effects of state shutdown and elective medical care suspensions on six different measures of the weekly volume of outpatient visits: 1) all outpatient visits; 2) cancer, heart disease, and diabetes visits; 3) musculoskeletal conditions visits; 4) mental health visits;

5) routine health and well-care visits; and 6) visits for chronic care procedures and laboratory tests (Cardiac Stress testing, Chemotherapy, Cancer Screenings, Diagnostic Imaging and A1C and other frequent blood tests). In the main analysis, we consider all outpatient visits for each health condition. In a sub-analysis, we distinguish between face-to-face vs. telemedicine visits for these 6 types of care.

We expect both the supply and demand side to behave differently towards health services that are are pressing, or are easier to conduct remotely. For example, patients might have inelastic demand for services related to the treatment of cancer, heart disease, and diabetes, and health care systems might prioritize those patients as well. Delaying treatment for those conditions could lead to substantial reductions in well-being and could increase mortality risks in the future. In contrast, the short run demand for well-care visits and medical check-ups might be fairly elastic. Many patients and providers will likely be willing to delay or even forego these scheduled visits in a given month without creating substantial health risks for the patient. It is plausible that state shutdown policies and elective medical procedure policies will have a smaller effect on the use of health services with inelastic demand and a larger effect on services with more elastic demand. In addition to studying whether visits happen, we also study whether procedures and tests are performed at visits to gauge impact on the intensity of care delivered in a visit. For each of the six outcomes, we first show an aggregate time series graph (the average across all states' total number of outpatient visits of a given type in each week from early January 2019 to mid May 2020). Second, we show event study plots: coefficients of the weekly leads and lags from a regression of the outcome against the state closure policy and elective medical procedure policy adoptions. Third, we present coefficient results from a generalized differences-in-difference (two-way fixed effect) regressions where all policy change variables enter the model at the same time. Both the event study models and the two-way fixed effects models are estimated using Poisson fixed effects regressions that include state fixed effects and week-of-year fixed effects. We estimate standard errors using a cluster robust variance matrix that allows for clustering at the state level.

5.1 Outpatient Visits

Figure 2 in the Appendix shows the average of states' total outpatient visit counts, by week, from the first week of January 2019 to second week of May, 2020. The vertical reference line in the graph separates the week of March 1st, 2020 from weeks since then. The graph makes it clear that there was a large and sudden decline in outpatient visits in March, 2020. The timing of the change in utilization makes some sense given the sequence of events leading to the epidemic. The first confirmed case of COVID-19 in the U.S. occurred on January 20th, 2020. But the first death was not announced until February 29th, 2020. The epidemic began to accelerate quickly from that point, and a national emergency was declared on March 13th, 2020.

From the the first week of March to its lowest point in early April, the average number of outpatient visits per week fell by almost 40 percent. Before the decline –in the first week of March – there were about 10,000 outpatient visits per week across the states in our sample. By the the second week of April, there were slightly less (6,000 visits) in the average state. The graph also shows that outpatient visits rebounded starting in the week of April 15th. Despite the recent increase in utilization, the average number of weekly outpatient visits remains well below the pre-COVID19 level as of May 15th, when the time series ends.

One goal of our paper is to understand how much of this decline was determined by state policies vs. private responses to changing epidemiological and economic conditions. The left panel of Figure 3 shows estimated coefficients and 95% confidence intervals from event study regression of outpatient visits on state fixed effects, week fixed effects, and a collection of eight weeks of pre-closure effects and six weeks of post-closure effects. The coefficients on the pre-policy effects are small and not statistically different from zero, supporting the assumption that there were no differential pre-trends or anticipation effects associated with timing of state closure decisions. In contrast, and consistent with a causal impact, the coefficients on the post-closure effects are negative and statistically different from zero at the 1 percent level, for the first two weeks following the closures.

The magnitude of the Figure 3 coefficients implies that state closure policies reduced outpatient visits by about 15-16 percent in the first two weeks of the shutdown. Although size of the coefficients remains relatively stable for a full six weeks after the state shutdown, the standard errors are much larger in the 4 later post-policy weeks and are not statistically significantly different from zero.

The right panel of Figure 3 shows estimated coefficients and 95% confidence intervals from the same event study regression, except here we focus on the second law included in this regression, whether/when the state suspended elective procedures. Again, there is no evidence of statistically significant pre-trends in outpatient visits. But unlike in the case of state closure policy, here there is no statistically significant evidence of a reduction in visits in the post-policy periods. We interpret this result with caution, as we can not rule out large positive or negative effects due to the magnitude of the standard errors. One possibility is that this maybe due to collinearity between the timing of the two policies (see Figure 1 for state policy timing; this shows that closure policies generally happened before states suspended elective procedures). When we estimate two event study models independently for each policy, the event study coefficients on the two weeks post state closure policies remain statistically significant and the coefficients on elective suspended remain imprecise.

Thus, the event study models suggest that the effect of the state closure policies was substantial, statistically significant in the two week window after the policy, and relatively stable over the full six week time horizon of our study. However, the event studies provide fairly inconclusive evidence on the effects of the elective procedure policies. In both cases, the event study models generally provide evidence in support of the common trends and no pre-trends assumptions that are required for the difference in difference model.

Given that the core DD assumptions seem plausible and the effects do not change much over the post-period, we next fit a standard DD model, which is a more restrictive regression specifications as the policy effects are forced to be constant per week after the policy change and the model imposes the assumption that there are no differential pre-trends in associated with state policy changes. This more parsimonious model allows us to examine the impact of more policies at the same time (for example, the state reopening policies).

The results of these DD regressions are in Table 7. The first column shows estimates from Poisson regressions of total outpatient visits in a state-week on state fixed effects, week fixed effects, state by week linear time trends and an indicator variable that turns on when the state adopts either a SAH mandate or a NEB shutdown mandate. The specification shown in the second column adds a DD term for state suspension of all elective medical procedures and provides for additional liability waivers. We also begin now to study the impact of reopenings. Table 7 's third column adds two DD term for state reopening policy: one for state lifting the SAH or NEB closure, and one for when it lifts the suspension on elective medical procedures. Across the three specifications, the models imply that when states adopt shutdown policies outpatient visits fell by 15 percent. This is consistent with evidence described above for the event study regression. In contrast, the estimated coefficients on the other policy variables in column three is small and not statistically different from zero.

Overall, evidence suggests that state closure policy lead to a 15% decrease in outpatient visits. This is a substantial effect. However, it explains less than half of the 40% decline outpatient visits during the early part of the epidemic.

Next, we break this result down by identifying which types of visits faced the largest drop and which types of visits were most impacted by these two focal policies; state closures and elective medical care suspended. We begin by presenting types of visits that are in theory less postponable or "inelastic", followed by visits assumed more postponable or "elastic".

Conceptually, chronic and time sensitive care for heart disease , diabetes and cancer may not fall significantly during the pandemic relative to services such as health checkups, orthopedic visits and mental health. However, the latter services may be possible to deliver through telehealth care (particularly mental health visits).

5.2 Cancer, Heart Disease, Diabetes

Figure 4 shows the cross-state average of total outpatient visit counts by week and type of care (visit reason) from the start of January 2019 to second week in May 2020. The first panel is for circulatory diseases which include all heart disease conditions. Here too, there is a clear large and sudden decline in outpatient visits in March 2020 and a sharp rebound in the week of April 15th. From the pre-epidemic period to the lowest point, average circulatory disease visits fell by almost percent 59%. Interestingly, the figure shows that as soon as visits rebound, they quickly reach their pre-pandemic levels again, suggesting there was some urgency in recovering this missed or delayed care.

We next show the event study estimates that trace out the effects of state closure policies, and elective or non-urgent care suspensions on circulatory disease visits. The left panel of Figure 5 shows estimated event study coefficients for pre and post state closure effects. Again here, the coefficients on the pre-policy effects are small and not statistically different from zero, supporting the assumption that there were no differential pre-trends or anticipation effects associated with timing of state closure decisions. In contrast, the coefficients on the post-closure effects are negative and statistically different from zero. The magnitude of these coefficients implies that state closure policies reduced circulatory disease visits by about 10% percent in the immediate three weeks following the shutdown and by approximately 20% in the sixth week post the shutdown.

The right panel of Figure 5 shows the event study coefficients pre and post the elective procedures suspended policy. Again, there is no evidence of statistically significant pre-trends. There is also no evidence of a statistically significant effect in the post-period. We note again here that the estimates are imprecise and that we can not distinguish a null from a zero finding.

Table 8 shows the difference in differences estimates. Across the three specifications, the models imply that state shutdown policies reduced outpatient visits for circulatory diseases by 11%. In contrast, the estimated coefficients on the other policy variables is small and not statistically different from zero. This result is in line with the evidence from the event study coefficients discussed above.

We also examine outpatient visits for diabetes, which affects 10% of the US population and 26% of the elderly.[23] The second panel in Figure 4 shows the cross-state average of total endocrine outpatient visits by week from the start of January 2019 to second week in May 2020. We see a very similar pattern to the decline and rebound in circulatory disease. Here too, a sharp decline from 1,400 visits per week on average, to 850 visits per week on average (a 40% decrease) and a sharp rebound in mid April. By the end of the time series, outpatient visits for endocrine related diseases had largely recovered to pre-epidemic levels.

The event study estimates in Figure 6 suggest that the state closure policies reduced endocrine outpatient visits by about 10%, immediately following the state closure. There is no evidence of differential pre-trends leading up to the state closures, and there is a clear downward slope exactly when the closure begins. The magnitude of the state closure effect on visits increases over time, reaching 22% by week 6 post closure. We find no evidence of elective procedure suspensions on endocrine visits. Table 8 shows the difference in differences estimates, and here the coefficients imply that when states adopt shutdown policies outpatient visits for Endocrine diseases decrease by 15% on average.

The final type of chronic care we examine is Neoplasms. This disease group includes metastatic cancers, benign tumors, and “in situ" malignant tumors. [24]The second row of Figure 4 shows the time series of the cross-state average of Neoplasm outpatient visit counts by week. There are two things to note about this figure. First, the average weekly visits for Neoplasms (at baseline) is far lower than the average weekly visits for Circulatory or Endocrine diseases, reflecting a lower count in Neoplasm patients overall. Second, from the pre-pandemic period to the lowest point, average Neoplasms visits fell by almost percent 63%. Neoplasm visits rebounded in mid-April. But unlike circulatory and endocrine visits, they had not recovered to pre-epidemic levels by May 15th.

Figure 7 shows estimated pre and post coefficients from the event study regression of outpatient Neoplasm visits. The coefficients on the pre-policy effects are small and not statistically different from zero. In contrast, the coefficients on the post-closure effects are negative and statistically different from zero. The magnitude of the effects of state closures on outpatient neoplasm visits is very large. The event study coefficients imply that the onset of state closure policies reduced visits by close to 50 percent in the first few weeks and by even more as time went on. Across states, neoplasm visits fell by about 63% in the initial

[23]According to the American Diabetes Association, in 2018, 10% of the US population (32.8 million) and 14.3 million seniors(26.8%) and in 2017, 270,000 deaths were attributed to diabetes.

[24]A majority of the ICD codes in this disease group however are for malignant tumors and only 7.8% are for benign tumors. We include benign tumors in our analysis because it is plausibly difficult for a patient to identify whether a tumor is benign or malignant before the visit.

part of the epidemic. The event study coefficients suggest that about 87% of that total decline is due to the state policy and 13% of the decrease is due to factors captured by date fixed effects. As with heart disease and diabetes, we find no evidence on an effect due to suspending elective procedures. Table 8 shows the difference in differences estimates, and here the coefficients imply that when states adopt shutdown policies, outpatient visits for Neoplasms decrease by 45% on average. Including the other policy variables does not alter this effect.

So far we have presented empirical results for all visits and three sets of chronic care visits (heart disease, diabetes and cancers). We next move onto sets of care we think are more postponable, such as orthopedic care and health checkups. We also examine mental health visits, and discuss how several factors may increase or decrease mental health visits during the pandemic period.

5.3 Musculoskeletal Diseases

Musculoskeletal diseases include a variety of conditions that differ in severity and pain levels, including non-chronic conditions such as sprains and strains and long term chronic conditions such as Arthritis and Rheumatic diseases. It is not obvious whether we should expect Musculoskeletal visits to be strongly vs. weakly affected by the shutdown. On one hand, over the counter and prescription pain relief medications can often help reduce Musculoskeletal pain; see Calvo-Alén (2010) for a review of RCT evidence. On the other hand, many patients receive physical therapy for Musculoskeletal conditions, which may or may not be compatible with telehealth visits.

The second row of Figure 4 shows the cross-state average of Musculoskeletal outpatient visit counts by week. Following a similar pattern as the other diseases, Musculoskeletal visits decline by 66% between the second week of March and Mid April. A rebound occurs after that, but until Mid May the level of visits does not return to its pre-pandemic level. Unlike Circulatory and Endocrine diseases, we do not see a rebound to original visit levels.

Figure 8 presents the event study estimates for Musculoskeletal outpatient visits. In the left panel, the coefficients on the pre-closure terms are small and not statistically different from zero, suggesting that the closures are not associated with differential pre-trends. In contrast, the event study coefficients become strongly negative after the onset of the state closure policies, suggesting that state closures induced a decline in outpatient visits for musculoskeletal conditions. The pattern of coefficients suggests that the effect of the closures grew over time, although the confidence intervals are wide on the later terms. The coefficients suggest that the closure policy reduced Musculoskeletal visits by about 50% percent in the first two weeks of the shutdown and a sizable 60% five weeks post the shutdown. Of all the conditions we have discussed so far, Musculoskeletal visits were most affected by the state closure policy. As with our other outcomes, we find no evidence that elective medical procedure policies had any additional impact on Musculoskeletal visits. Table 9 shows the difference in differences estimates, and here the coefficients imply that when states adopt shutdown policies, outpatient visits for Musculoskeletal diseases decline by about 65% on average. The coefficient is statistically significant and is not attenuated when we include other state policies.

5.4 Mental Health

Next, we discuss trends in outpatient visits for mental and behavioral health. It is important to examine this disease category since mental disorders are the leading cause of disability in the United States, accounting for 18.7% of all years of life lost to disability and premature mortality (Murray et al., 2013). The third row of Figure 4 shows the cross-state average of mental and behavioral health visit counts by week from the start of January 2019 to second week in May 2020. There are two things to note about this Figure. First, mental and behavioral health visits decline by only 31% during the early part of the epidemic. This is by far the smallest decline across the disease groups we have so far examined. Second, mental health visits rebound to near pre-epidemic levels by Mid May. As mentioned earlier, descriptive statistics from Medicare (Verma, 2020) and other EMR data (Mehrotra et al., 2020) have signaled that many people were able to receive mental health services using telehealth modalities during the epidemic. This could explain the smaller decline in the number of mental health visits.

Next, Figure 9 presents the event study coefficients for the effect of state closure and elective procedure suspensions. Overall, we find no evidence that either type of state policy affected mental and behavioral health visits. We interpret the results here with caution however. Since the magnitude of the total decline is somewhat smaller than other conditions (31% here vs 50-60% in other visit types), we maybe unable to detect, say, a 2-5% decrease in visits due to the state policies.

Table 9 shows the difference in differences estimates, and much like the event study results, we do not detect an effect of the state policies on mental health visits. It is worth noting that given the magnitude of the standard error on the state closure coefficient, we are unable to detect an effect below approximately 8%.

5.5 Health Checkups

A final type of visits we examine combines all visits for routine health checkups, routine follow-up care, immunization and prenatal care visits.[25] This groups of visits includes both visits that do not necessarily require adequately timed care (such as well-care visits), and visits that require adequately timed care (such as prenatal care). The bottom right panel of Figure 4 shows the cross-state average of health status and check-up visit counts by week. The figure shows that checkup visits decreased by 55% between mid March and mid April before rebounding slightly. By May 15th, the weekly number of check-up visits remains below pre-pandemic level.

Figure 10 presents the event study estimates. In the left panel, the coefficients on the pre-closure terms are small and statistically insignificant, supporting the assumption that there are no differential pre-trends associated with the timing of state closure policies. In contrast, the coefficients on the post-closure terms are large, negative, and statistically significantly different from zero. The event study suggests that state closure policies did lead to substantial reductions in the number of health status check-ups per week and the negative effect grew with time since the policy change. The coefficients suggest that the closure policy reduced checkup visits by about 20% percent in the first two weeks of the shutdown and by closer to 50% in the five weeks after the shutdown. In contrast, there is little evidence that state elective medical procedure suspensions had a substantial effect on outpatient visits for basic check-ups. Table 9 shows the relevant difference in differences estimates. These estimates suggest that the state closure policy lead to a 20% decrease in these health checkup visits.

The evidence so far suggests that most visit types faced declines in visits due to the state closure policies. However, the magnitude of the effect varies across visit types. The effect of the state closure policy is strongest for care that, ex ante, might be considered the easiest to postpone or even forego entirely, such as Musculoskeletal visits and routine health checkups. However, the shutdown also had large negative effects on outpatient visits for care that might be harder to defer safely, such as Neoplasms. Our results suggest that state closure policies were associated with a 50-60% decline in visits related to Neoplasms. On the other hand, decreases in visits for Diabetes and Heart Disease were somewhat weakly connected to the state closure policy. The state policy was associated with only a 10-12% decline in visits for these two disease groups. Finally, we find no evidence that states which suspended elective

[25] This group of visits is described by the ICD chapters as "Factors influencing health status and contact with health services". Because in this group, testing for infectious diseases is included, we excluded the ICD10 code Z11 for screening examination for infectious and parasitic diseases, to avoid picking up covid19 related care.

procedures had larger declines in visits than states that did not order suspending elective procedures. Nor do we find evidence that states that introduced medical liability waivers had different levels of visits that those that did not add these waivers.

To understand whether telehealth played a role in fending off the decrease in visits, we provide preliminary descriptive evidence in figures 11 and 12. In figure 11 we plot the weekly count of visits that are explicitly coded as telehealth visits. The graph documents a huge spike in the number of telehealth visits in the data. There were almost no telehealth prior to the pandemic, and a sharp surge when the pandemic begins. Although the graph looks dramatic, the magnitude of the increase in telehealth visits is small relative to all outpatient visits. We observed only 83,000 telehealth specific visits in our data between March and May 2020. One possibility is that many physicians are providing health care remotely without specifically using the telehealth coding scheme when entering data, as guidance specifically allows them to do that for a large number of codes. To overcome this issue, we divided visits into either telehealth eligible or not telehealth eligible based on the visit code. Figure 12, shows clearly how codes not eligible for telehealth declined far more than telehealth eligible codes. Interestingly, services not eligible for telehealth rebound faster as well during the recovery.

5.6 Laboratory Tests and Outpatient Procedures

The results so far are focused on various types of outpatient visits. In this section, we examine a selection of specific outpatient procedures and laboratory exams.

Figure 13 shows the cross-state average count of all laboratory exams by week. The weekly average fell from about 11,000 laboratory exams per week to about 9,000 laboratory exams per week during the early weeks of the shutdown. These lab orders exclude activities related to COVID-19 testing or testing for infectious diseases. As with outpatient visits, the volume of lab tests also rebound in mid April but remain below the pre-pandemic levels.

Figure 14 shows estimated coefficients and 95% Confidence Intervals from event study regressions. The coefficients on the pre-policy effects are small and not statistically different from zero, supporting the assumption that there were no differential pre-trends or anticipation effects associated with timing of state closure decisions. States that ultimately closed were not running more labs in advance of the closure policies. In contrast, the coefficients on the post-closure effects are negative and statistically different from zero. The magnitude of these coefficients implies that state closure policies reduced lab orders by over 20% in the three weeks immediately following the shutdown and by 30% 6 weeks post the shutdown.

Panel A of table 10 presents the difference in differences models. There are two things to note in table 10. First, much like the event study estimates, state closure policies are associated with a 25-30% decrease in total laboratory tests. Second, states that added medical liability waivers to protect physicians from malpractice saw larger declines in laboratory tests during the period that electives procedures were suspended. The model suggests that medical liability waivers reduced lab tests by 28-30%. These results may suggest that health care provider order few laboratory tests when they have additional liability protection. We also examined specific types of procedures and laboratory tests: (1) blood tests, including tests for A1C, LDL, HDL, Cholesterol, Triglyceride, Lipid and Complete Blood Panel tests; (2) Cancer therapy procedures, which include intravenous chemotherapy administration via infusion, radiation therapy or oral chemotherapy administration in the physician's office; (3) Cancer screenings, which include PAP smear tests, Prostate-Specific Antigen (PSA) tests, Mammograms, Endoscopes and Colonoscopies for Cancer screening; (4) Cardiac stress testing, which includes Echocardiography and tread mill testing; and (5) all diagnostic imaging except chest imaging, which we exclude because it might be COVID-19 related. For brevity, we do not discuss each group separately but provide an overall summary of the evidence here.

Blood tests (Figure 15) decline substantially during the shutdown, but a significant rebound. Cancer Therapy (Figure 16), cancer screenings (Figure 17), cardiac stress testing (Figure 18) and diagnostic imaging (Figure 19) show especially large drops and small rebounds. The smallest rebound is for cancer therapy. One possible explanation is that is that the modality of cancer therapy may have changed. For example, it is possible that more patients are receiving oral administration at home. Another possibility is that some patients are forgoing certain types of procedures. For example, Vordermark (2020) summarized expert recommendations on the role of radiotherapy during the COVID-19 epidemic and found that omission of radiotherapy was recommended by physicians in elderly patients with low-risk breast cancer and in early-stage lymphoma.

To understand how much of this decline is attributable to the state policies, figures 20 - 24 show the event study coefficients on state closure and electives suspended for each of these categories. We find significant decreases in these procedures and labs due to the state closure policies. The biggest by far is in the diagnostic imaging services. The event study coefficients imply reductions of around 60%. The only service that did not seem to be impacted by the state closure is cancer therapy. We find little evidence that elective procedure suspensions affect the number of procedures and labs, despite targeting specifically procedures and labs. However, we still interpret these results cautiously because the confidence intervals are wide.

Finally, Table 10 and Table 11 present difference in differences coefficients for procedures and labs. These coefficients are in line with the evidence from the event study estimates. The difference in difference models also point towards state closures contributing to the decline in procedures and labs. The biggest decline by far due to the state policy, is for diagnostic imaging. In addition, the coefficient on medical liability waivers is negative and significant for two of the five groups of services (blood tests and cancer therapy). Taken together, there is a consistent pattern indicating that state closures and that medical liability waivers may have decreased outpatient labs and procedures.

6 Conclusion

The U.S. health care system has performed a large and vital role while under much duress since early March 2020 as it pivoted to providing life-saving care for COVD-19 patients. But there are signs some forms of non-COVID-19 care has declined, and this experience must be understood for designing health care access policies that maximize population health. We examine near-real time data from a nationwide electronic healthcare records system that covers over 35 million patients to provide novel evidence of how non-COVID19 acute care and preventive/primary care are affected during the policy and private responses to the COVID-19 epidemic. We find that state closure policies are associated with large declines in ambulatory visits, with varying effects by type of care. However, closure policy does not explain all of the decline in visits that occurred after the first week of March 2020. We see substantial and impressive rebounding of visit volume in more recent months, although care visits still remain below the pre-epidemic levels in most cases and policy efforts to sustain health care access is ongoing.

In an effort to provide timely research evidence, we use real-time health care records that have been made newly available on a pro-bono basis for research, and are not from established research resources and involve a number of limitations that should be kept in mind. One is that the universe from which these data are drawn might change over time as more practices adopt electronic health records or switch into this particular health care electronic database management system. Although we do not expect that it would change at the same time as state laws, it affects our over-time comparisons. We address this partially using a balanced panel of the same providers/organizations, but there is still changing composition of patient populations possible. There are also various pitfalls possible to using the still-fairly-novel-resources of electronic health records in the health economics and policy literature. Much future work remains, both in examining these same questions with more established resources, and in understanding the future health consequences of changes in health care use from this era.

Tables and Figures

Table 1: Summary Statistics of Patients Registered in Healthjump Data

Patient Characteristics	Mean	St. Dev
Female	0.523	0.499
Age	53.76	54.46
Age < 18	0.063	0.244
Age 18-64	0.56	0.495
Age 65+	0.352	0.477
Non- Hispanic White (among non-missing)	0.805	0.396
Non- Hispanic Black (among non-missing)	0.162	0.369
Other Race (among non-missing)	0.03	0.176
Race missing	0.706	0.455
Hispanic (among non-missing)	0.095	0.293
Ethnicity missing	0.585	0.478
Total Number of Unique Patients	35,143,966	

Notes- The unit of observation is a registered patient. A patient need not have had an encounter during our study period in order to be currently registered in the system. Age is calculated as date of birth subtracted from July 2020.

Table 2: Patient Characteristics for Patients Registered in Health Jump Data v. NAMCS

	HealthJump 2019		NAMCS 2016	
Patient Characteristics	Mean	St dev	Mean	St dev
Female	0.58	0.49	0.57	0.49
Age	52.8	21.96	45.1	25.4
Age $<$ 18	0.1	0.29	0.21	0.4
Age 18-64	0.53	0.49	0.52	0.49
Age 65+	0.35	0.047	0.27	0.44
Non- Hispanic White (among non-missing)	0.82	0.38	0.83	0.37
Non- Hispanic Black (among non-missing)	0.15	0.36	0.11	0.31
Other (among non-missing)	0.02	0.14	0.05	0.22
Hispanic (among non-missing)	0.12	0.33	0.17	0.37
Number of Observations	18,256,548		13,165	

Notes – The table compares the HealthJump sample of patients with at least one outpatient visit in 2019 to The National Ambulatory Medical Care Survey (NAMCS) sample of patients in 2016 (weighed by the number of patient visits).

Table 3: Summary Statistics of Patient Visits Between Jan 1 2019 and June 30 2020

	Q1 2019	Q2 2019	Q3 2019	Q4 2019	Q1 2020	Q2 2020
Patient Characteristics	Mean	Mean	Mean	Mean	Mean	Mean
Female	0.58	0.586	0.586	0.582	0.58	0.586
Age	51.98	53.15	52.96	53.32	53.29	54.73
Age $<$ 18	0.1	0.087	0.093	0.1	0.875	0.062
Age 18-64	0.54	0.539	0.539	0.527	0.53	0.548
Age 65+	0.339	0.353	0.347	0.351	0.361	0.368
Non- Hispanic White (among non-missing)	0.828	0.823	0.821	0.823	0.819	0.814
Non- Hispanic Black (among non-missing)	0.151	0.156	0.158	0.156	0.161	0.168
Other (among non-missing)	0.02	0.02	0.02	0.019	0.019	0.017
Race Missing	0.43	0.432	0.432	0.421	0.426	0.343
Hispanic (among non-missing)	0.129	0.123	0.12	0.114	0.115	0.113
Total Number of Visits	4,070,368	4,359,389	4,622,696	5,204,095	5,178,123	3,739,569

The unit of observation is the patient visit level. We use records from Jan 1 2019 to June 30 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits (WV, WA, UT, TX, TN, SC, PA, OR, OK, OH, NY, NV, NJ, NC, MS, MO, MN, MI, MD, LA, KY, KS, IL, GA, FL, DE, CO, AZ, AR, AL, AK); we also remove visits that are COVID-19 related, and visits on weekends and special holidays (Memorial Day 2019, July 4th 2019, Labor Day 2019, Thanksgiving 2019, Christmas 2019 and New Year's Eve 2019, New Year's Day 2019 and 2020 and Memorial day 2020). These sample restrictions leads to 27,174,240 visits.

Table 4: Summary Statistics of Visits, by State, Jan 1 2019 - June 30 2020

State	Female	Age	Age<18	Age 18-64	Age 65+	White	Black	Other Race	Hispanic	Number of Visits	State Population	% population	% visits	% visits/% pop
AK	0.54	53.41	0.06	0.61	0.31	0.939	0.05	0.012	0.063	184,006	731,545	0.22	0.7	3.16
AL	0.6	58.39	0.04	0.5	0.44	0.71	0.283	0.007	0.037	1,638,644	4,903,185	1.49	6.27	4.2
AR	0.6	48.11	0.15	0.55	0.28	0.721	0.269	0.01	0.136	1,145,760	3,017,804	0.92	4.38	4.77
AZ	0.56	67.75	0.02	0.27	0.69	0.935	0.038	0.026	0.177	792,138	7,278,717	2.22	3.03	1.37
CA	0.57	57.22	0.05	0.54	0.39	0.846	0.061	0.093	0.254	734,879	39,512,223	12.04	2.81	0.23
CO	0.57	51.17	0.08	0.59	0.31	0.979	0.007	0.015	0.141	357,409	5,758,736	1.75	1.37	0.78
CT	0.54	46.83	0.04	0.75	0.2	0.964	0.022	0.014	0.526	4,734	3,565,287	1.09	0.02	0.02
DC	0.57	47.4	0.03	0.75	0.19	0.763	0.174	0.063	0.171	554	705,749	0.22	0	0.01
DE	0.57	58.81	0.03	0.5	0.44	0.89	0.098	0.012	0.032	434,213	973,764	0.3	1.66	5.6
FL	0.56	60.97	0.07	0.38	0.53	0.926	0.059	0.015	0.075	425,606	21,477,737	6.54	1.63	0.25
GA	0.56	51.51	0.12	0.54	0.32	0.759	0.224	0.017	0.102	1,015,752	10,617,423	3.23	3.89	1.2
HI	0.56	50.33	0.02	0.52	0.42	0.737	0.078	0.184	0.234	575	1,415,872	0.43	0	0.01
IA	0.37	61.37	0.03	0.46	0.49	0.986	0.003	0.012	0.097	79,867	3,155,070	0.96	0.31	0.32
ID	0.58	52.81	0.06	0.54	0.37	0.821	0.173	0.006	0.03	3,555	1,787,065	0.54	0.01	0.02
IL	0.6	47.95	0.14	0.55	0.29	0.961	0.032	0.007	0.012	427,904	12,671,821	3.86	1.64	0.42
IN	0.57	55.03	0.09	0.5	0.39	0.937	0.04	0.024	0.196	247,898	6,732,219	2.05	0.94	0.46
KS	0.6	48.72	0.14	0.54	0.3	0.822	0.161	0.017	0.021	901,418	2,913,314	0.89	3.45	3.88
KY	0.57	52.75	0.1	0.54	0.34	0.544	0.446	0.01	0.151	741,481	4,467,673	1.36	2.84	2.08
LA	0.59	47.44	0.15	0.56	0.27	0.89	0.098	0.012	0.032	176,3420	4,648,794	1.42	6.75	4.77
MA	0.61	48.27	0.04	0.64	0.32	0.847	0.061	0.093	0.055	2,610	6,892,503	2.1	0.01	0
MD	0.57	52.74	0.07	0.58	0.34	0.927	0.067	0.006	0.023	132,705	6,045,680	1.84	0.51	0.28
ME	0.62	55.37	0.06	0.48	0.45	0.971	0.008	0.021	0.068	675	1,344,212	0.41	0	0.01
MI	0.57	54.08	0.08	0.52	0.37	0.984	0.009	0.007	0.011	478,526	9,986,857	3.04	1.83	0.6
MN	0.59	55.52	0.05	0.55	0.38	0.964	0.01	0.026	0.046	231,555	5,639,632	1.72	0.89	0.52
MO	0.73	49.64	0.05	0.67	0.27	0.926	0.056	0.018	0.006	628,051	6,137,428	1.87	2.4	1.28
MS	0.61	48.36	0.14	0.58	0.27	0.51	0.475	0.015	0.281	1,426,331	2,976,149	0.91	5.46	6.02
MT	0.56	60.78	0.05	0.34	0.6	0.98	0.02	0	0.03	1,041	1,068,778	0.33	0	0.01
NC	0.59	55.5	0.09	0.49	0.41	0.833	0.153	0.014	0.085	2,629,245	10,488,084	3.2	10.06	3.15
ND	0.53	58.41	0.02	0.51	0.45	0.959	0.02	0.02	0.053	1,172	762,062	0.23	0	0.02
NE	0.5	56.03	0.05	0.46	0.47	0.962	0.003	0.035	0.066	731	1,934,408	0.59	0	0
NH	0.58	54.55	0.02	0.48	0.48	0.987	0.008	0.005	0.058	671	1,359,711	0.41	0	0.01
NJ	0.57	57.86	0.03	0.54	0.4	0.88	0.082	0.038	0.116	2,108,393	8,882,190	2.71	8.07	2.98
NM	0.57	61.59	0.07	0.34	0.57	0.967	0.014	0.018	0.55	18,230	2,096,829	0.64	0.07	0.11
NV	0.54	56.3	0.05	0.55	0.38	0.576	0.306	0.118	0.594	132,396	3,080,156	0.94	0.51	0.54
NY	0.58	49.75	0.06	0.67	0.25	0.885	0.087	0.028	0.352	272,589	19,453,561	5.93	1.04	0.18
OH	0.59	60.75	0.05	0.41	0.52	0.945	0.046	0.01	0.015	509,245	11,689,100	3.56	1.95	0.55
OK	0.61	56.86	0.06	0.5	0.41	0.937	0.047	0.015	0.039	236,816	3,956,971	1.21	0.91	0.75
OR	0.56	58.8	0.02	0.53	0.42	0.923	0.018	0.059	0.105	152,175	4,217,737	1.28	0.58	0.45
PA	0.56	58.8	0.02	0.53	0.42	0.86	0.108	0.032	0.167	2,704,514	12,801,989	3.9	10.35	2.65
RI	0.68	54.68	0	0.47	0.53	0.941	0.034	0.025	0.05	369	1,059,361	0.32	0	0
SC	0.57	58.61	0.05	0.5	0.43	0.765	0.227	0.008	0.035	414,784	5,148,714	1.57	1.59	1.01
SD	0.52	66.57	0.01	0.26	0.71	0.998	0.002	0	0.023	2,461	884,659	0.27	0.01	0.03
TN	0.59	57.81	0.05	0.51	0.42	0.828	0.168	0.004	0.011	414,893	6,829,174	2.08	1.59	0.76
TX	0.57	54.31	0.1	0.49	0.4	0.903	0.076	0.022	0.345	1,125,324	28,995,881	8.83	4.3	0.49
UT	0.57	46.42	0.13	0.61	0.25	0.965	0.012	0.023	0.137	1,537,775	3,205,958	0.98	5.88	6.02
VA	0.61	49.51	0.08	0.65	0.25	0.955	0.039	0.006	0.05	189,755	8,535,519	2.6	0.73	0.28
VT	0.6	55.42	0.01	0.51	0.46	0.997	0.003	0	0.127	447	623,989	0.19	0	0.01
WA	0.56	58.34	0.04	0.52	0.42	0.958	0.014	0.028	0.051	544,063	7,614,893	2.32	2.08	0.9
WI	0.55	55.95	0.01	0.6	0.37	0.904	0.076	0.02	0.032	3,466	5,822,434	1.77	0.01	0.01
WV	0.62	44.37	0.17	0.59	0.23	0.935	0.057	0.008	0.034	1,339,607	1,792,147	0.55	5.12	9.39
WY	0.52	51.36	0.06	0.68	0.23	0.972	0.008	0.021	0.08	13,260	578,759	0.18	0.05	3.48

Notes- The unit of observation is the patient visit level. Age is calculated as date of birth subtracted from the visit date. We use records from Jan 2019 to June 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020, and exclude visits related to COVID-19. State population as of July 1 2019 from https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html obtained from the first table in Excel list. Note that '% population' should be interpreted as the number of visits divided by population and expressed as a percent, rather than that the sample contains this percent of a state's residents.

Table 5: Summary Statistics of Visit Reason by ICD9/10 and Visit Duration at the State – Week Level Between Jan 1 2019 and June 30 2020

Visit Reason	Mean	St. Dev	Min	Max
All Visits	10951	9635	119	53021
Circulatory	1314	1795	0	8966
Endocrine	1749	2236	0	10219
Neoplasms	625	777	3	4093
Musculoskeletal	2509	2499	28	14433
Mental and Behavioral Health	973	1305	0	6242
Health Status and Checkups	2766	3127	3	14473
Visit Duration				
Less than 15 minutes	0.296	0.456	0	1
15 to 29 minutes	0.074	0.262	0	1
30 or more minutes	0.3	0.458	0	1
Number of Visits	27,281,029			

Notes- The unit of observation is the state-week count level (for all except the last row which represent the uncollapsed visit counts). Visits are classified based on the 9th or 10th revision of the International Statistical Classification of Disease and Related Health Problems Chapters. We use records from Jan 1 2019 to June 30 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits on weekends and special holidays. These sample restrictions leads to 27,281,029 visits

Table 6: Summary Statistics of Laboratory Exams and Outpatient Procedures at the State – Week Level Between Jan 1 2019 and June 30 2020

	Mean	St. Dev	Min	Max
All Labs	12810	23379	0	127998
Blood Tests (A1C/LDL/HDL/cholesterol/Triglyceride, Lipid and Complete Blood Panel)	812	1266	0	6946
Chemotherapy (IV/Infusion, Radiation or Oral Administration)	156	219	0	6946
Cancer Screening (PAP, PSA, Mammogram, and Endo/Colonoscopy)	131	199	0	1023
Cardiac Stress Test	90	150	0	617
All Diagnostic Imaging (Except Chest)	324	388	0	2038
Total Number of Visits with at least one Lab order	3,244,145			
Total Number of Visits with at least one Outpatient Procedure	17,793,417			

Notes- The unit of observation is the state-week-count level (except for the last 2 rows which show the uncollapsed totals). Laboratory groups are classified based on the CPT code or the LOINC code of the lab order. Outpatient procedures are defined using HCPCS/CPT codes. We use records from Jan 1 2019 to June 30 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays (Memorial Day 2019, July 4th 2019, Labor Day 2019, Thanksgiving 2019, Christmas 2019 and New Year's Eve 2019, New Year's Day 2019 and 2020 and Memorial day 2020). These sample restrictions leads to 17,793,417 visits with at least one outpatient procedure and 3,244,145 visits with at least one lab order.

Table 7: Estimates of the Effect of State Policies on Total Visits Between Jan 1st 2019 and May 15th 2020

Weekly Total Visits	Model 1	Model 2	Model 3
State Closure	-0.166**	-0.170**	-0.168**
	(0.056)	(0.06)	(0.058)
Elective Medical Suspended		-0.035	-0.04
		(0.072)	(0.074)
Added Liability Waivers		-0.032	-0.043
		(0.044)	(0.044)
State Reopen			0.033
			(0.065)
Elective Medical Reopen			0.06
			(0.058)
Observations	2046	2046	2046

Notes: The unit of observation is the state- week level. Model 1 estimates the effect of state closure on visits. Model 2, adds the effect of elective procedures being suspended and medical liability waivers issued during the pandemic. Model 3, adds the effect of state reopening and elective medical procedures allowed to resume. We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays. All regressions include state fixed effects, date fixed effect and state linear year trend. Standard errors have been constructed allowing for non-independence of observations within a state. + p-value <0.1, * 0.05 < p-value<=0.01, ** p <= 0.01

Table 8: Estimates of the Effect of State Policies on Total Visits by Reason for Visit (ICD Code) Between Jan 1st 2019 and May 15th 2020

Circulatory	Model 1	Model 2	Model 3
State Closure	-0.107**	-0.117***	-0.117**
	(0.036)	(0.044)	(0.043)
Elective Medical Suspended		-0.008	-0.011
		(0.063)	(0.064)
Added Liability Waivers		-0.043	-0.052
		(0.038)	(0.04)
State Reopen			0.03
			(0.039)
Elective Medical Reopen			0.026
			(0.048)
Endocrine			
State Closure	-0.146**	-0.152**	-0.154**
	(0.037)	(0.042)	(0.04)
Elective Medical Suspended		-0.034	-0.034
		(0.065)	(0.063)
Added Liability Waivers		-0.015	-0.02
		(0.038)	(0.041)
State Reopen			0.059
			(0.042)
Elective Medical Reopen			-0.0005
			(0.05)
Neoplasms			
State Closure	-0.451**	-0.455**	-0.455**
	(0.058)	(0.059)	(0.058)
Elective Medical Suspended		0.054	0.028
		(0.146)	(0.139)
Added Liability Waivers		-0.006	-0.013
		(0.079)	(0.079)
State Reopen			0.221
			(0.169)
Elective Medical Reopen			0.104
			(0.09)
Observations	2046	2046	2046

Notes: The unit of observation is the state- week level. Model 1 estimates the effect of state closure on visits. Model 2, adds the effect of elective procedures being suspended and medical liability waivers issued during the pandemic. Model 3, adds the effect of state reopening and elective medical procedures allowed to resume.We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays. All regressions include state fixed effects, date fixed effect and state linear year trend. Standard errors have been constructed allowing for non-independence of observations within a state. + p-value <0.1, * 0.05 < p-value<=0.01, ** p <= 0.01

Table 9: Estimates of the Effect of State Policies on Total Visits by Reason for Visit (ICD Code) Between Jan 1st2019 and May 15th

Musculoskeletal	Model 1	Model 2	Model 3
State Closure	-0.605**	-0.610**	-0.649**
	(0.097)	(0.099)	(0.094)
Elective Medical Suspended		-0.0027	-0.04
		(0.181)	(0.173)
Added Liability Waivers		-0.035	-0.043
		(0.11)	(0.173)
State Reopen			0.251
			(0.178)
Elective Medical Reopen			0.151
			(0.137)
Mental and Behavioral Health			
State Closure	-0.057	-0.06	-0.061
	(0.038)	(0.041)	(0.041)
Elective Medical Suspended		-0.004	-0.002
		(0.06)	(0.059)
Added Liability Waivers		-0.016	-0.012
		(0.033)	(0.033)
State Reopen			0.011
			(0.024)
Elective Medical Reopen			-0.018
			(0.023)
Health Status and Checkups			
State Closure	-0.195**	-0.196**	-0.201**
	(0.05)	(0.048)	(0.046)
Elective Medical Suspended		-0.07	-0.067
		(0.079)	(0.077)
Added Liability Waivers		0.0121	0.006
		(0.057)	(0.061)
State Reopen			0.132*
			(0.068)
Elective Medical Reopen			-0.02
			(0.061)
Observations	2046	2046	2046

Notes: The unit of observation is the state- week level. Model 1 estimates the effect of state closure on visits. Model 2, adds the effect of elective procedures being suspended and medical liability waivers issued during the pandemic. Model 3, adds the effect of state reopening and elective medical procedures allowed to resume. We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays. All regressions include state fixed effects, date fixed effect and state linear year trend. Standard errors have been constructed allowing for non-independence of observations within a state. + p-value <0.1, * 0.05 < p-value<=0.01, ** p <= 0.01

Table 10: Estimates of the Effect of State Policies on Laboratory Tests & Cancer Screening Between Jan 1st2019 and May 15th

	(1)	(2)	(3)
All Labs			
State Closure	-0.290**	-0.373**	-0.336**
	(0.1093)	(0.0878)	(0.0647)
Elective Medical Suspended		-0.054	-0.067
		(0.0666)	(0.0732)
Added Liability Waivers		-0.329**	-0.364**
		(0.1042)	(0.1156)
State Reopen			0.075+
			(0.0446)
Elective Medical Reopen			0.170+
			(0.0914)
Blood Tests			
State Closure	-0.116	-0.187*	-0.186*
	(0.076)	(0.0812)	(0.077)
Elective Medical Suspended		-0.014	-0.013
		(0.0902)	(0.0898)
Added Liability Waivers		-0.207*	-0.218+
		(0.0963)	(0.1244)
State Reopen			0.099
			(0.0667)
Elective Medical Reopen			0.016
			(0.113)
Cancer Screening			
State Closure	-0.248**	-0.306**	-0.305**
	(0.0872)	(0.1150)	(0.1128)
Elective Medical Suspended		-0.088	-0.091
		(0.0833)	(0.0859)
Added Liability Waivers		-0.164	-0.171
		(0.1038)	(0.1282)
State Reopen		0.079	0.071
		(0.1173)	(0.1216)
Elective Medical Reopen			0.023
			(0.1318)
Observations	2042	2042	2042

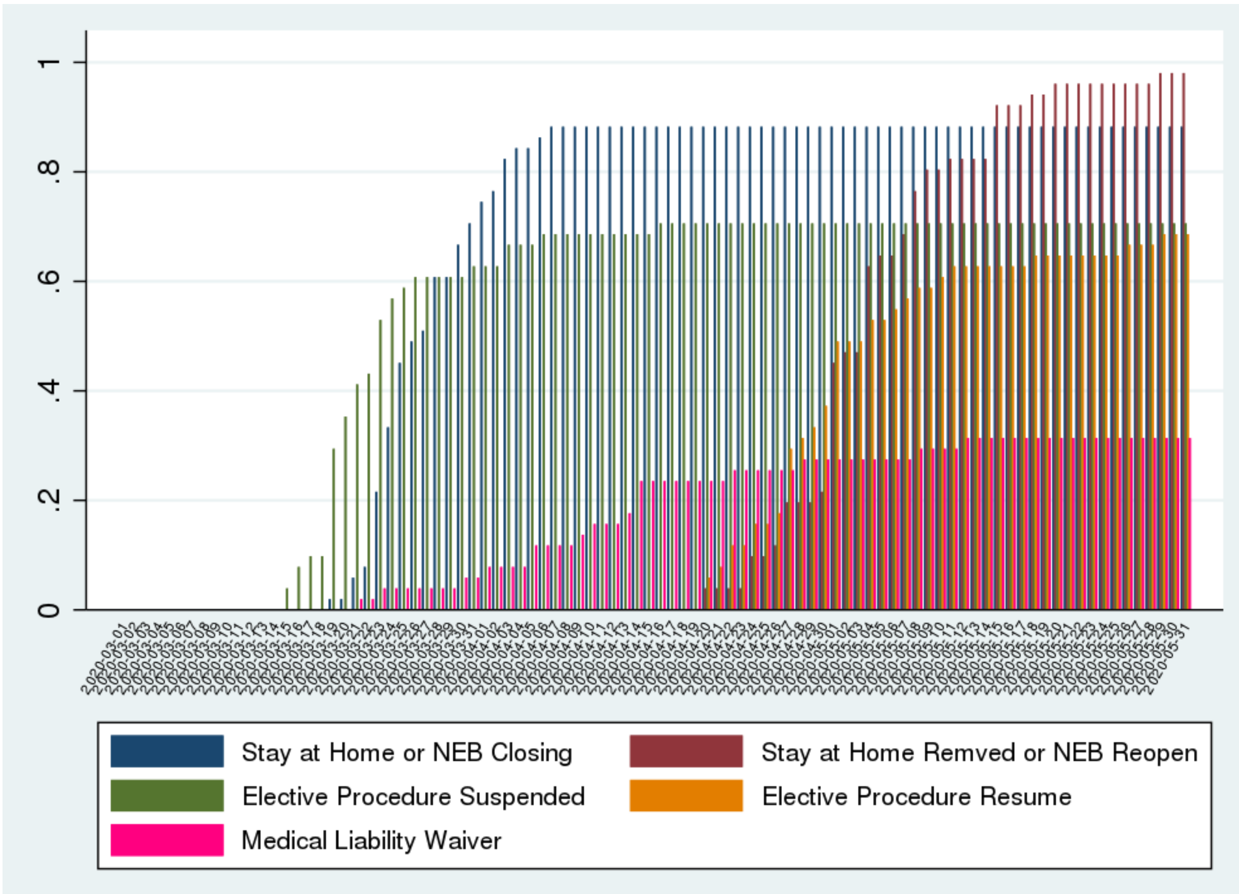
Notes: The unit of observation is the state- week level. Model 1 estimates the effect of state closure on visits. Model 2, adds the effect of elective procedures being suspended and medical liability waivers issued during the pandemic. Model 3, adds the effect of state reopening and elective medical procedures allowed to resume.We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays. All regressions include state fixed effects, date fixed effect and state linear year trend. Standard errors have been constructed allowing for non-independence of observations within a state. + p-value <0.1, * 0.05 < p-value<=0.01, ** p <= 0.01

Table 11: Estimates of the Effect of State Policies on Outpatient Procedures Between Jan 1st 2019 and May 15th 2020

	(1)	(2)	(3)
Cancer Therapy			
State Closure	0.093	0.036	0.034
	(0.0941)	(0.0792)	(0.0826)
Elective Medical Suspended		-0.111	-0.107
		(0.1309)	(0.1263)
Added Liability Waivers		-0.261*	-0.247*
		(0.1197)	(0.1192)
State Reopen			0.012
			(0.1341)
Elective Medical Reopen			-0.047
			(0.0932)
Cardiac Stress Test			
State Closure	-0.348**	-0.368**	-0.357**
	(0.087)	(0.0536)	(0.0544)
Elective Medical Suspended		-0.18	-0.192+
		(0.1112)	(0.1149)
Added Liability Waivers		-0.185	-0.216
		(0.1155)	(0.1419)
State Reopen			0.011
			(0.1298)
Elective Medical Reopen			0.168
			(0.1413)
Diagnostic Imaging except Chest			
State Closure	-0.548*	-0.625*	-0.617*
	(0.2769)	(0.2608)	(0.2679)
Elective Medical Suspended		0.049	0.141
		(0.2767)	(0.2467)
Added Liability Waivers		-0.442	-0.353
		(0.3883)	(0.3476)
State Reopen			0.680**
			(0.2267)
Elective Medical Reopen			-0.113
			(0.1498)
Observations	2042	2042	2042

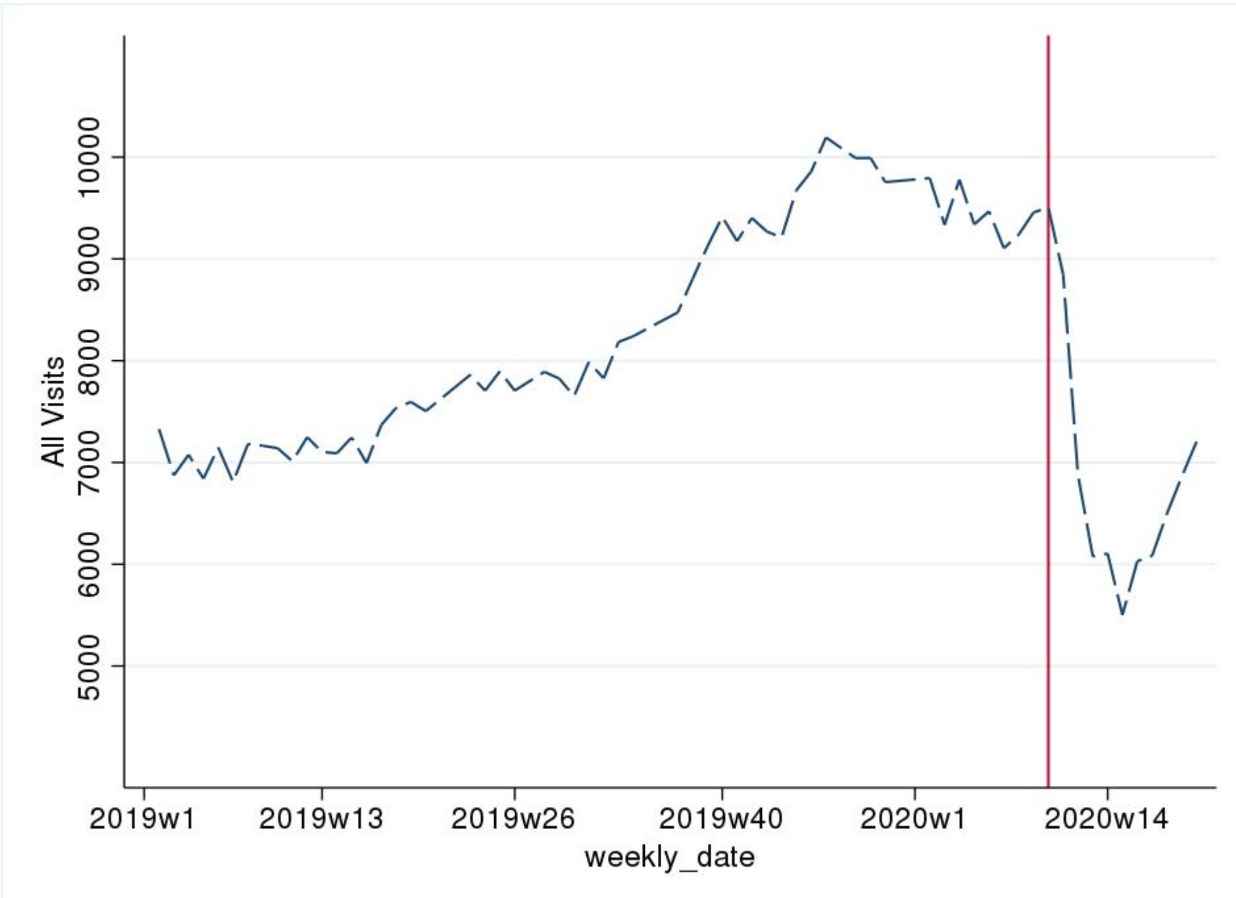
Notes: The unit of observation is the state- week level. Model 1 estimates the effect of state closure on visits. Model 2, adds the effect of elective procedures being suspended and medical liability waivers issued during the pandemic. Model 3, adds the effect of state reopening and elective medical procedures allowed to resume. We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays. All regressions include state fixed effects, date fixed effect and state linear year trend. Standard errors have been constructed allowing for non-independence of observations within a state. + p-value <0.1, * 0.05 < p-value<=0.01, ** p <= 0.01

Figure 1: States Policies Over Time Between March 1st 2020 and May 31st 2020



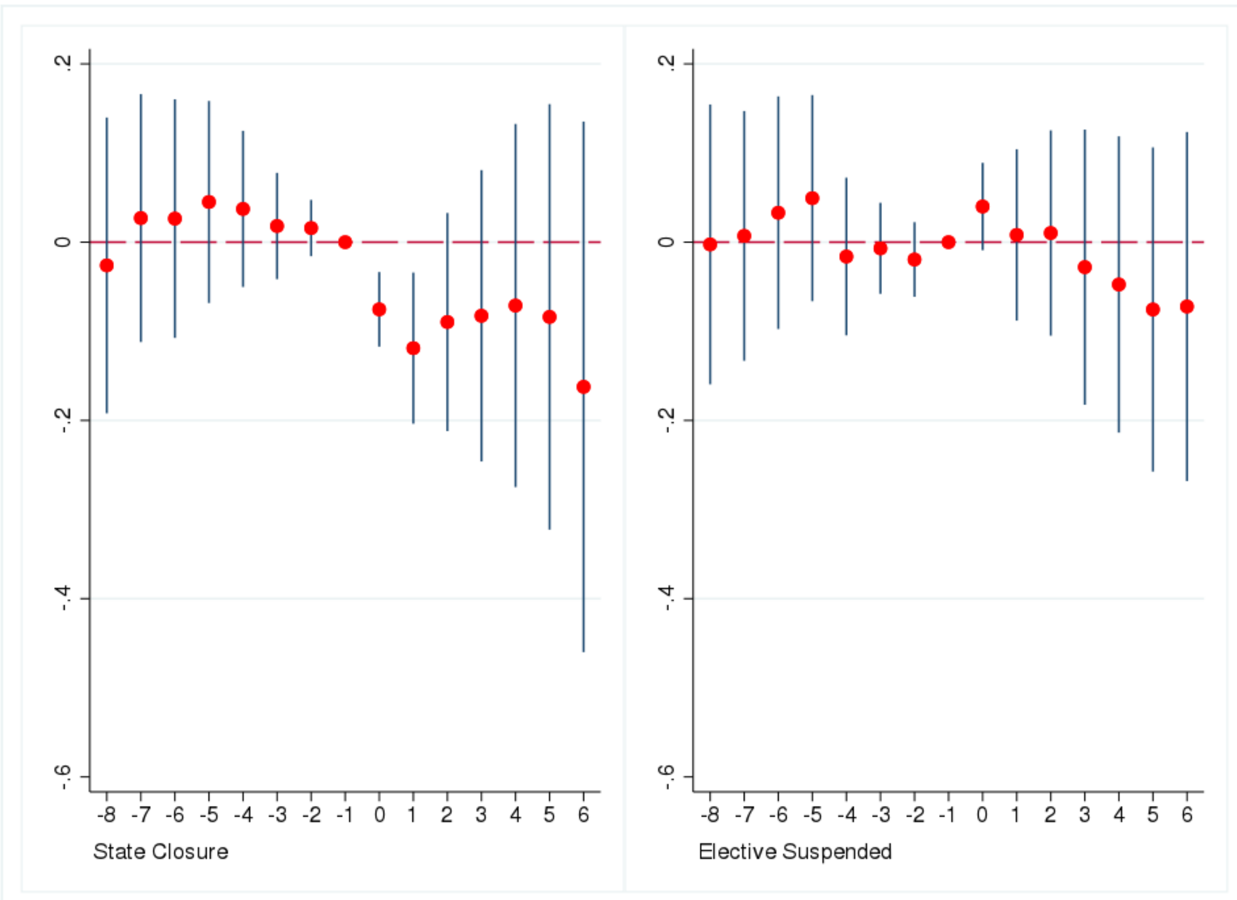
Notes - The unit of observation is the state - day. See Appendix Table A.1 for policy dates used in constructing this Figure.

Figure 2: Trends in Weekly Outpatient Visits Between Jan 1st 2019 and May 15th 2020



Notes - We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 3: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on All Outpatient Visits Jan 1st 2019 – May 15th 2020



Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 4: Trends in Weekly Outpatient Visits by Visits Reason Between Jan 1st 2019 and May 15th 2020

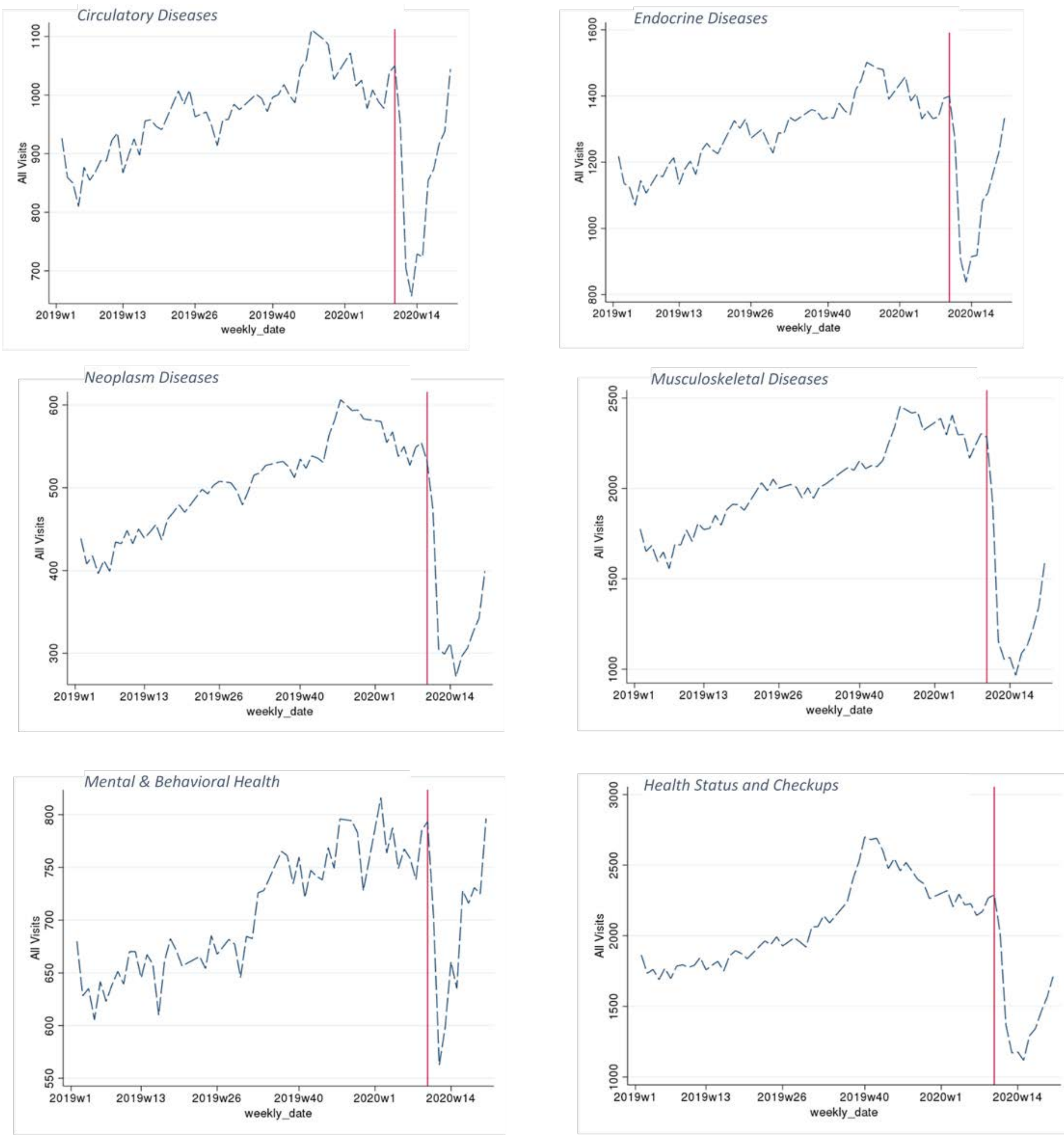
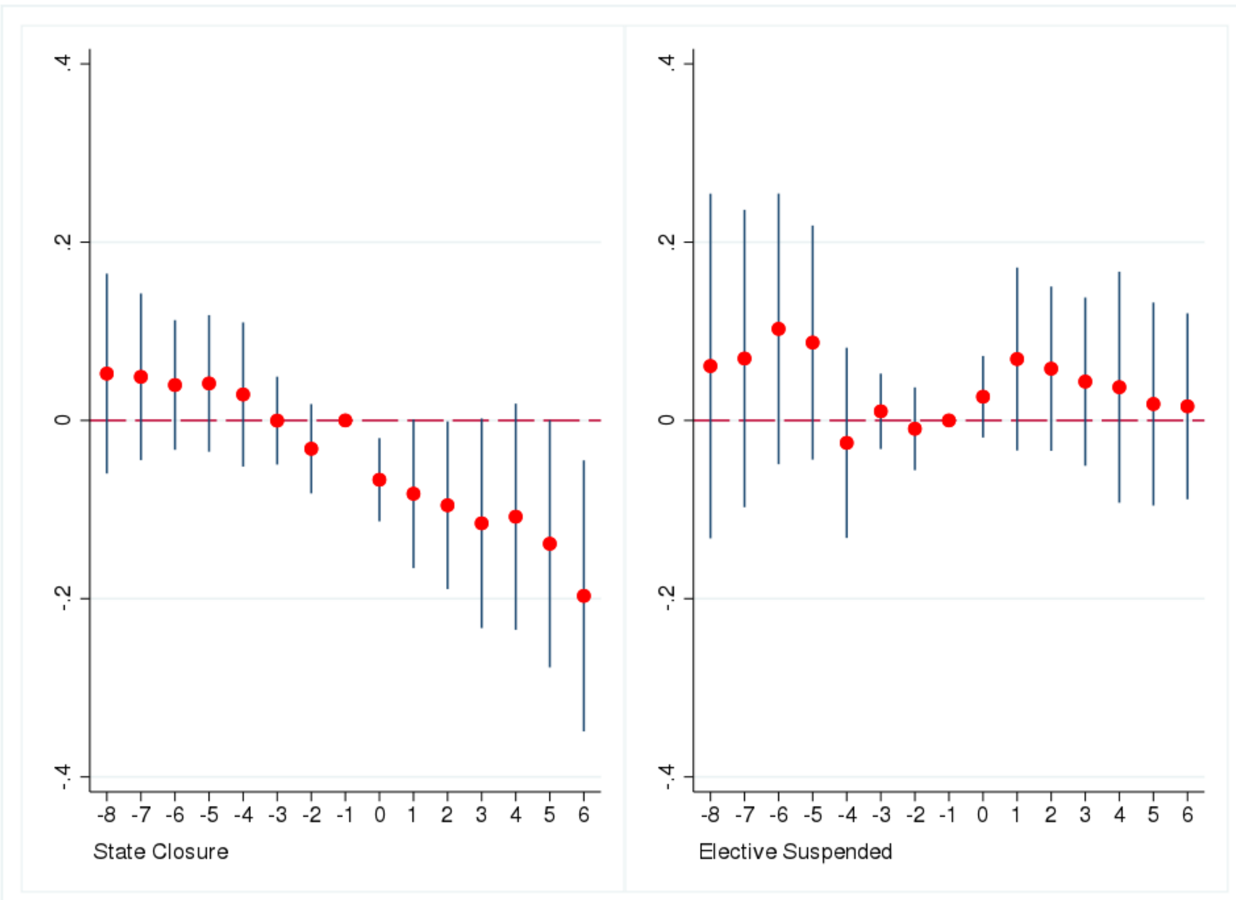
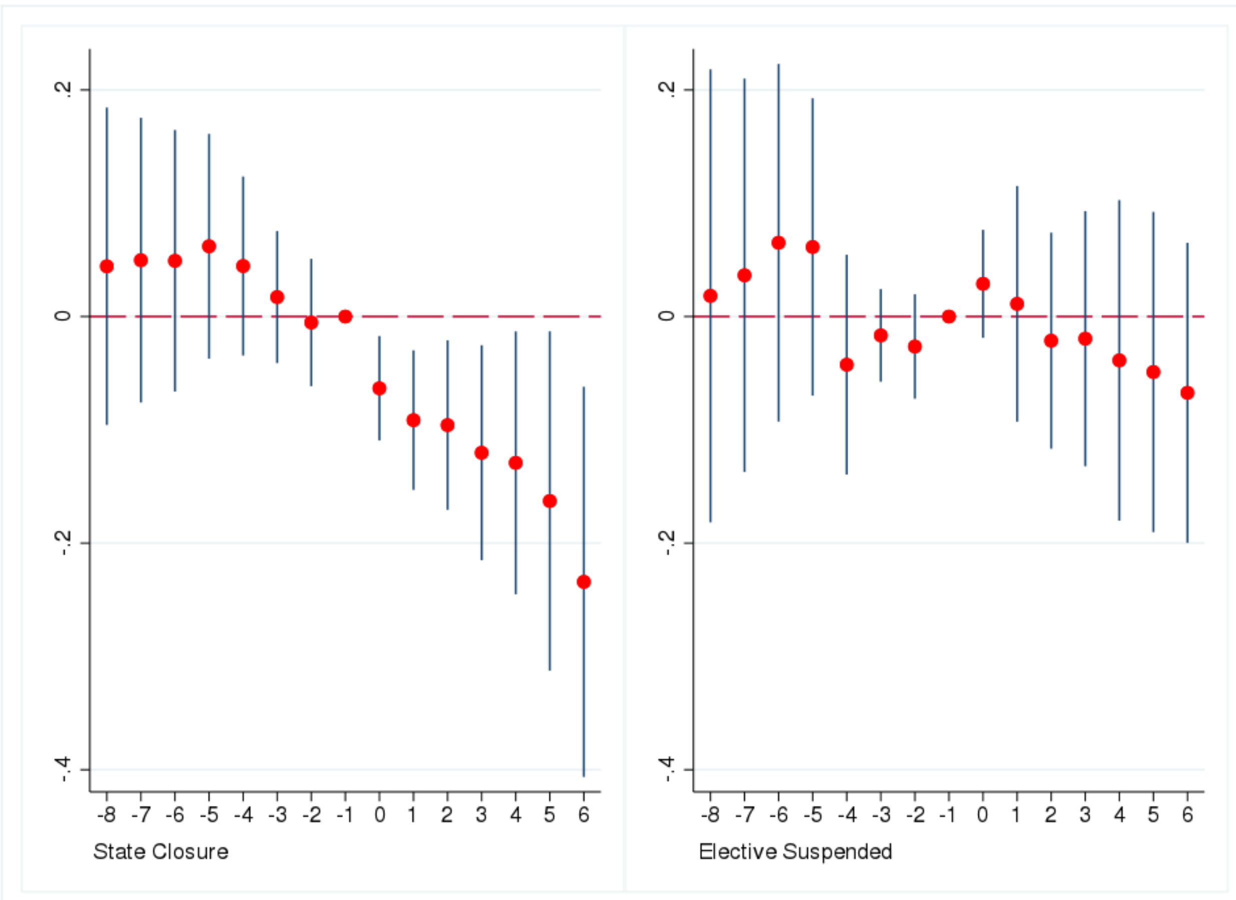


Figure 5: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Circulatory Diseases Outpatient Visits Jan 1st 2019 – May 15th 2020



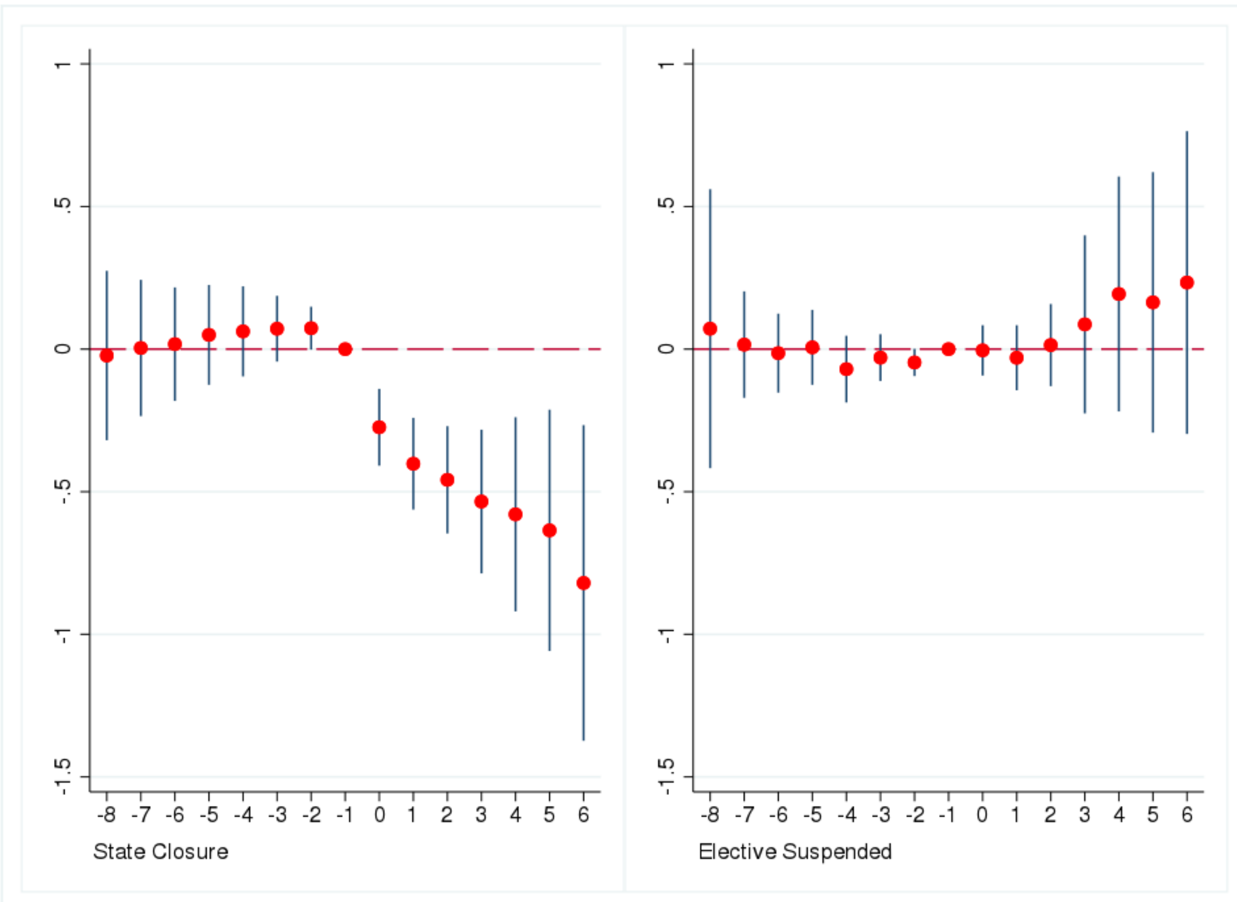
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 6: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Endocrine Diseases Outpatient Visits Jan 1st 2019 – May 15th 2020



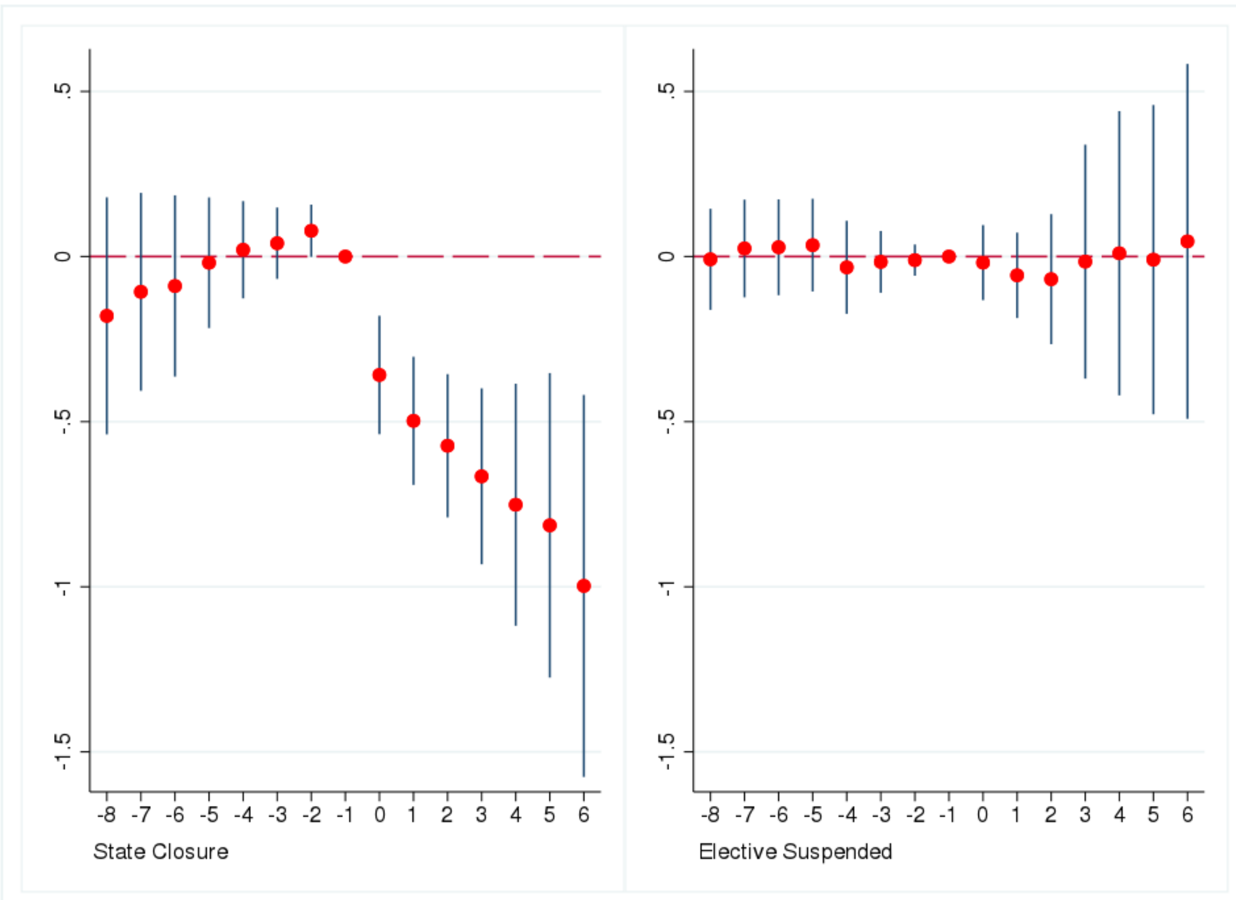
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 7: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Neoplasms Outpatient Visits Jan 1st 2019 – May 15th 2020



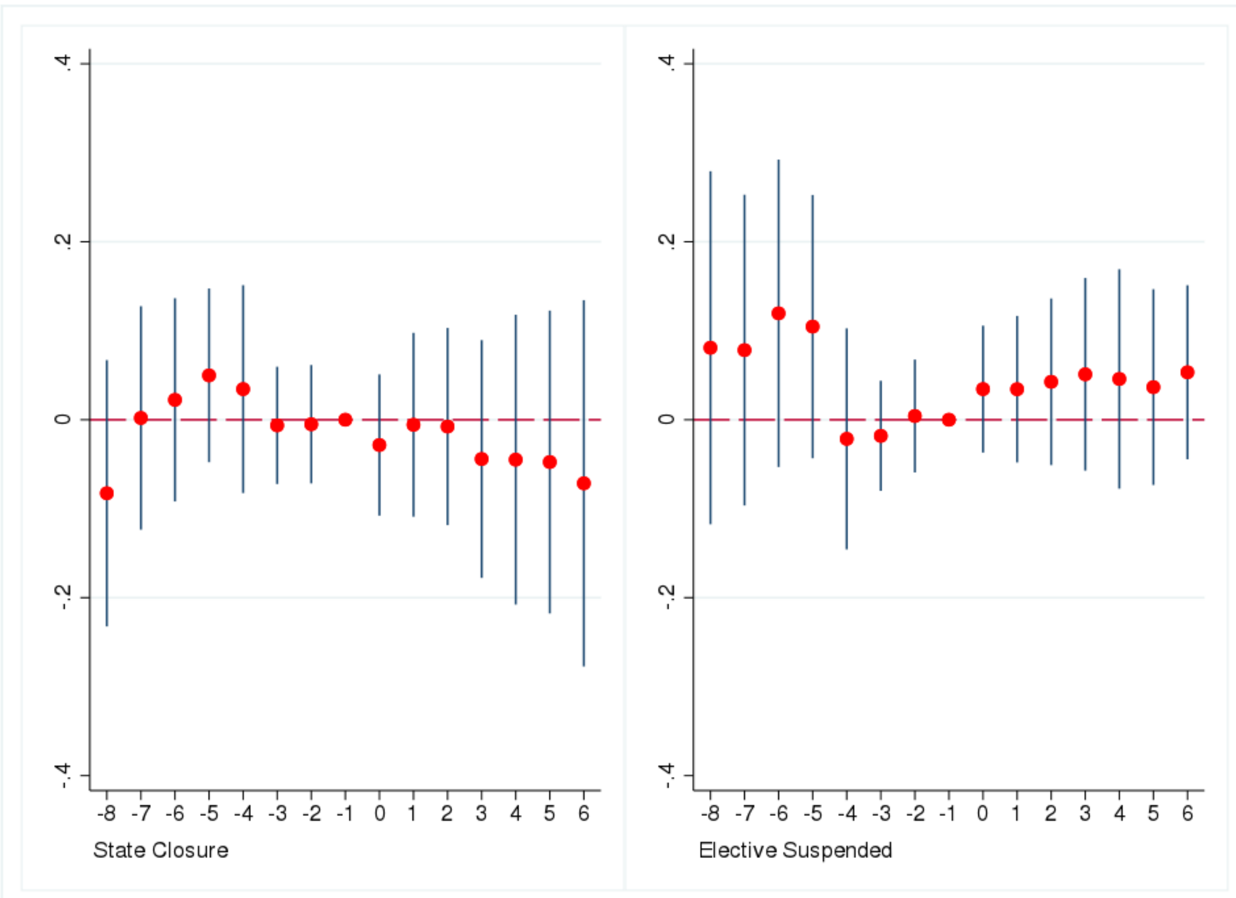
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 8: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Musculoskeletal Outpatient Visits Jan 1st 2019 – May 15th 2020



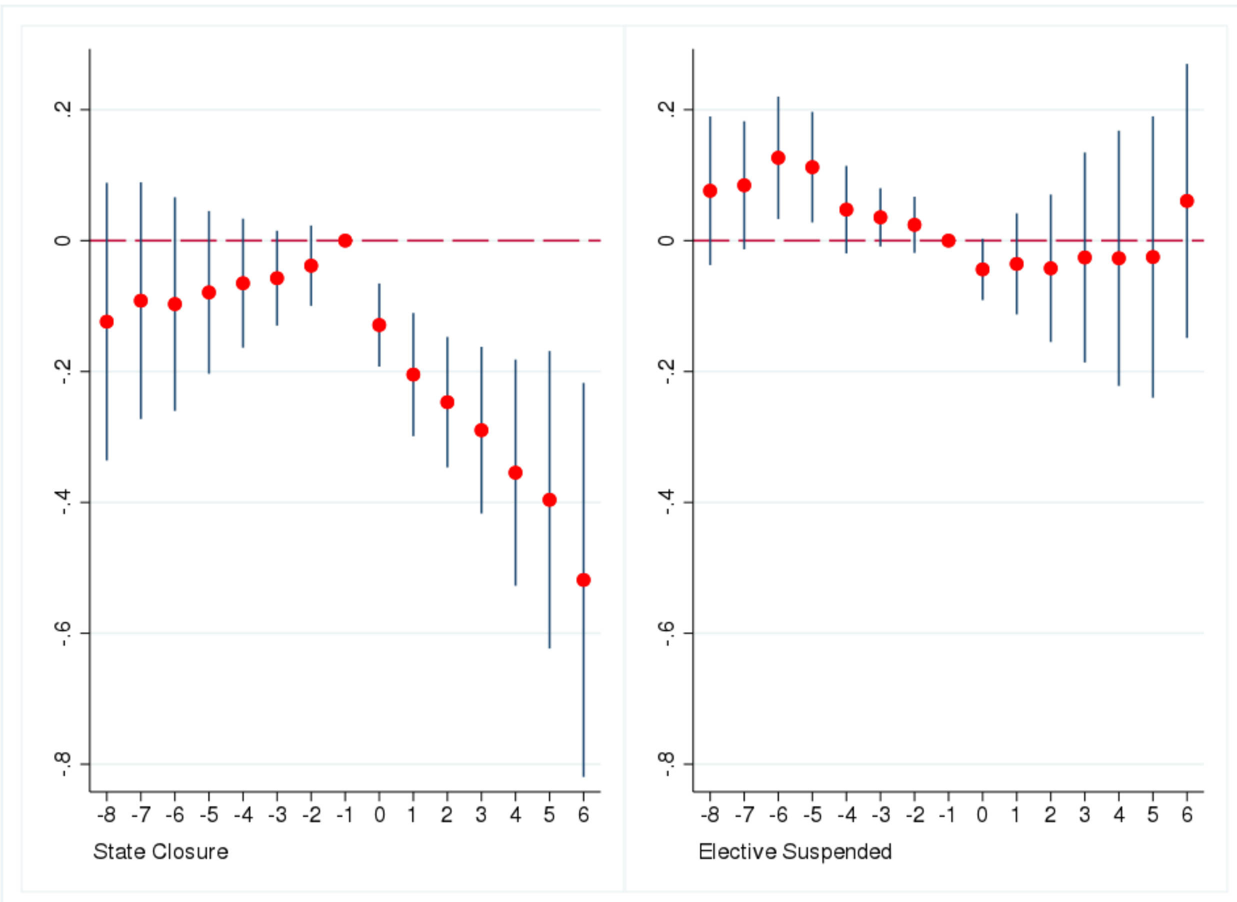
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 9: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Mental and Behavioral Health Outpatient Visits Jan 1st 2019 – May 15th 2020



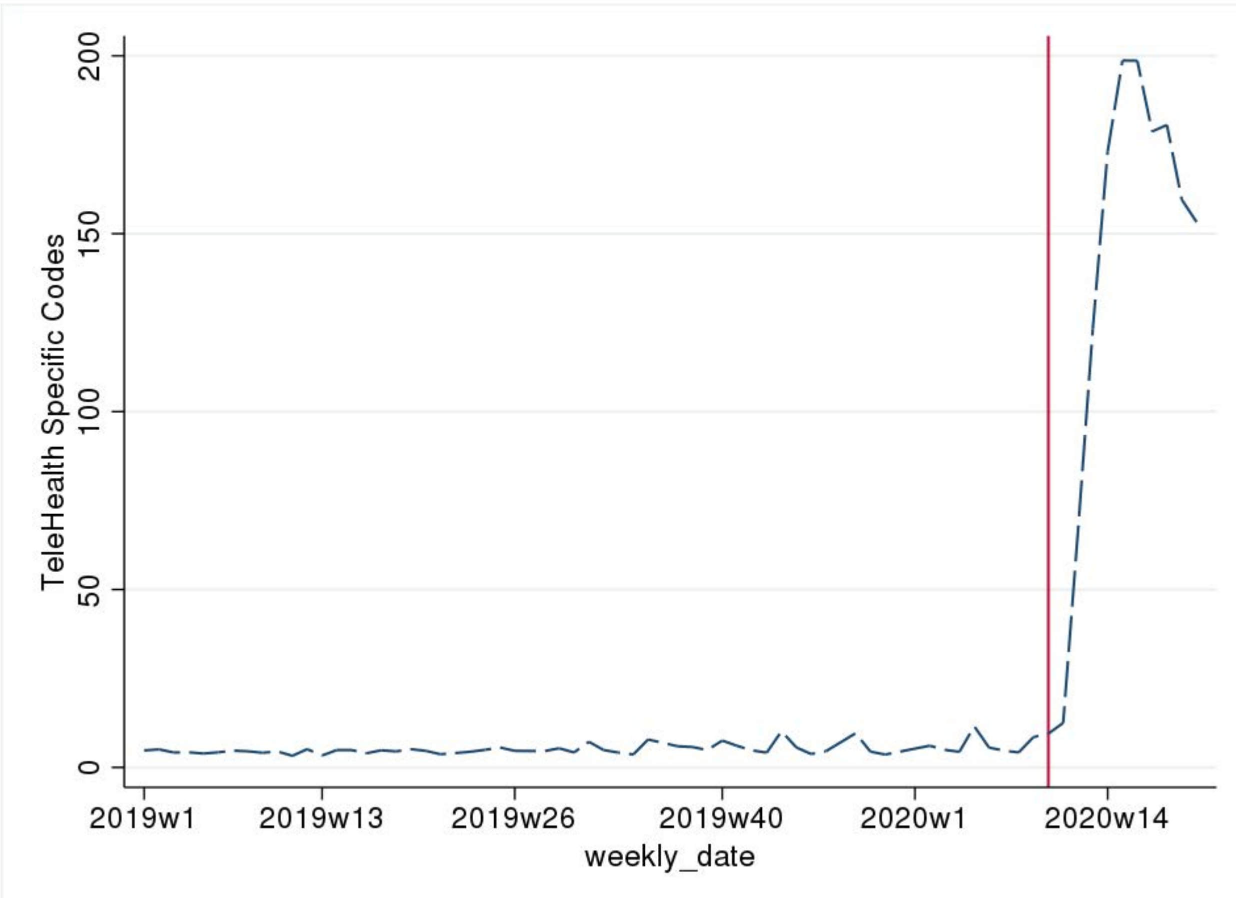
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 10: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Health Status and Checkup Visits Jan 1st 2019– May 15th 2020



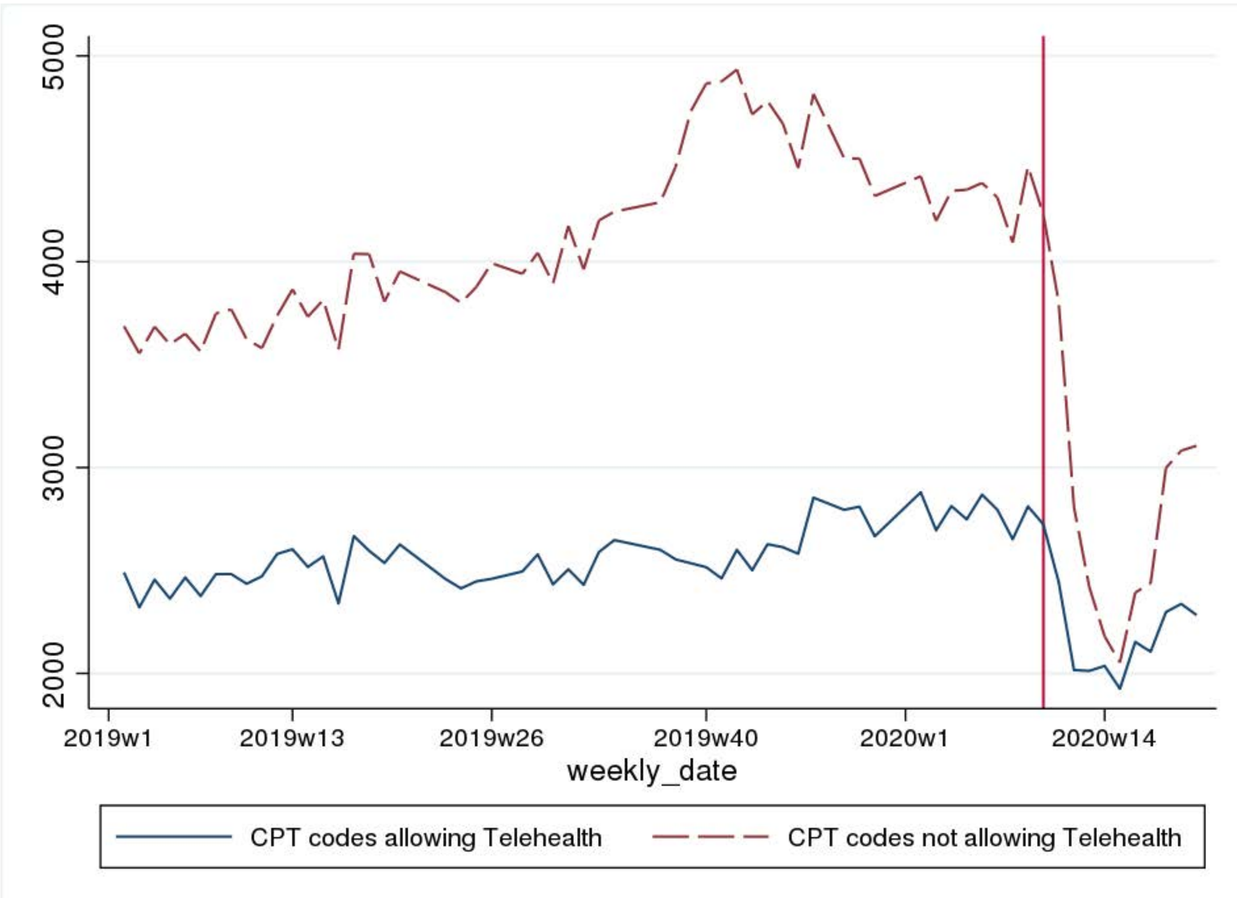
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 11: State-Week Trends in Telehealth Visits Using the Narrow Definition of Services Eligible for TeleHealth



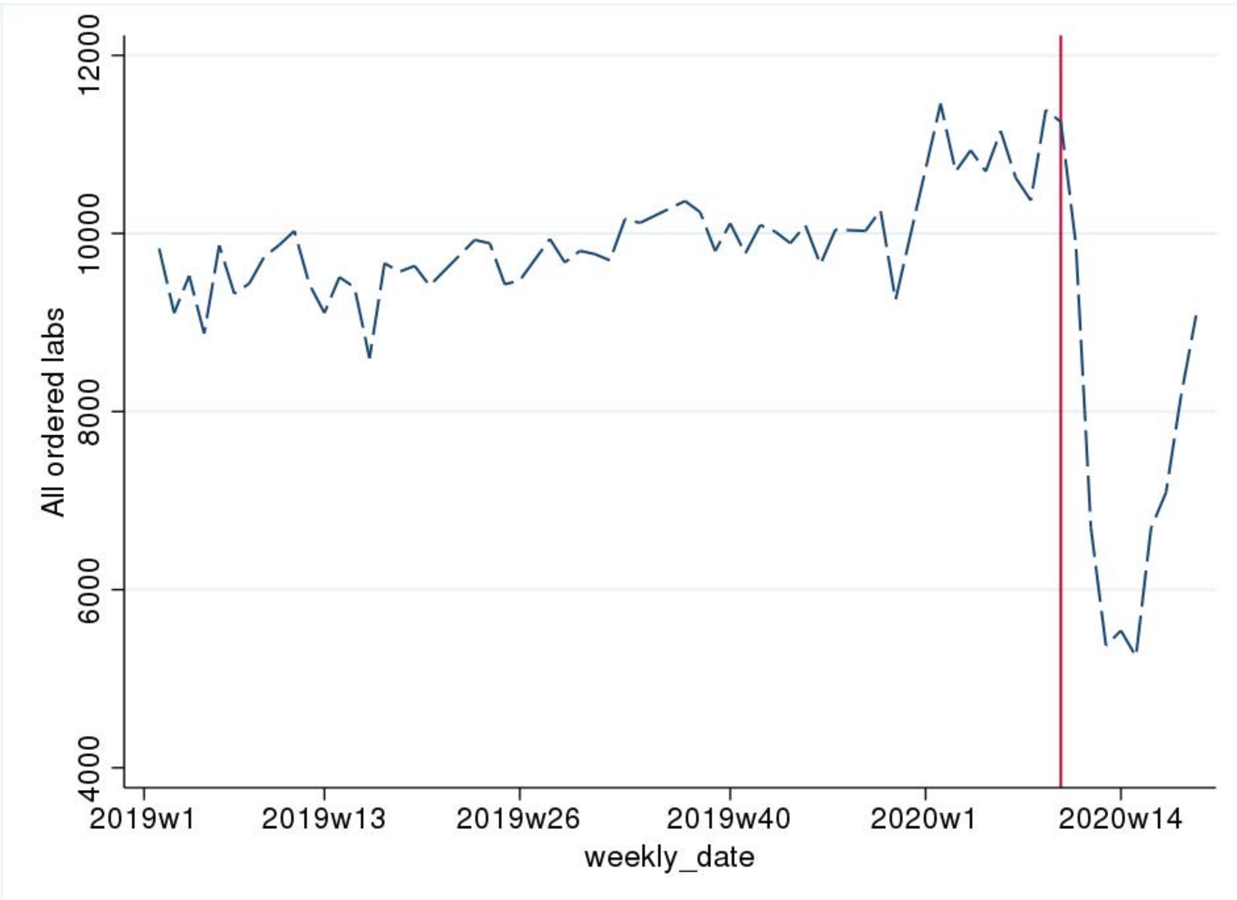
Notes-We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 12: State Week Trends in Visits with Service Codes Eligible for Tele Health Vs Not Eligible for Tele Health



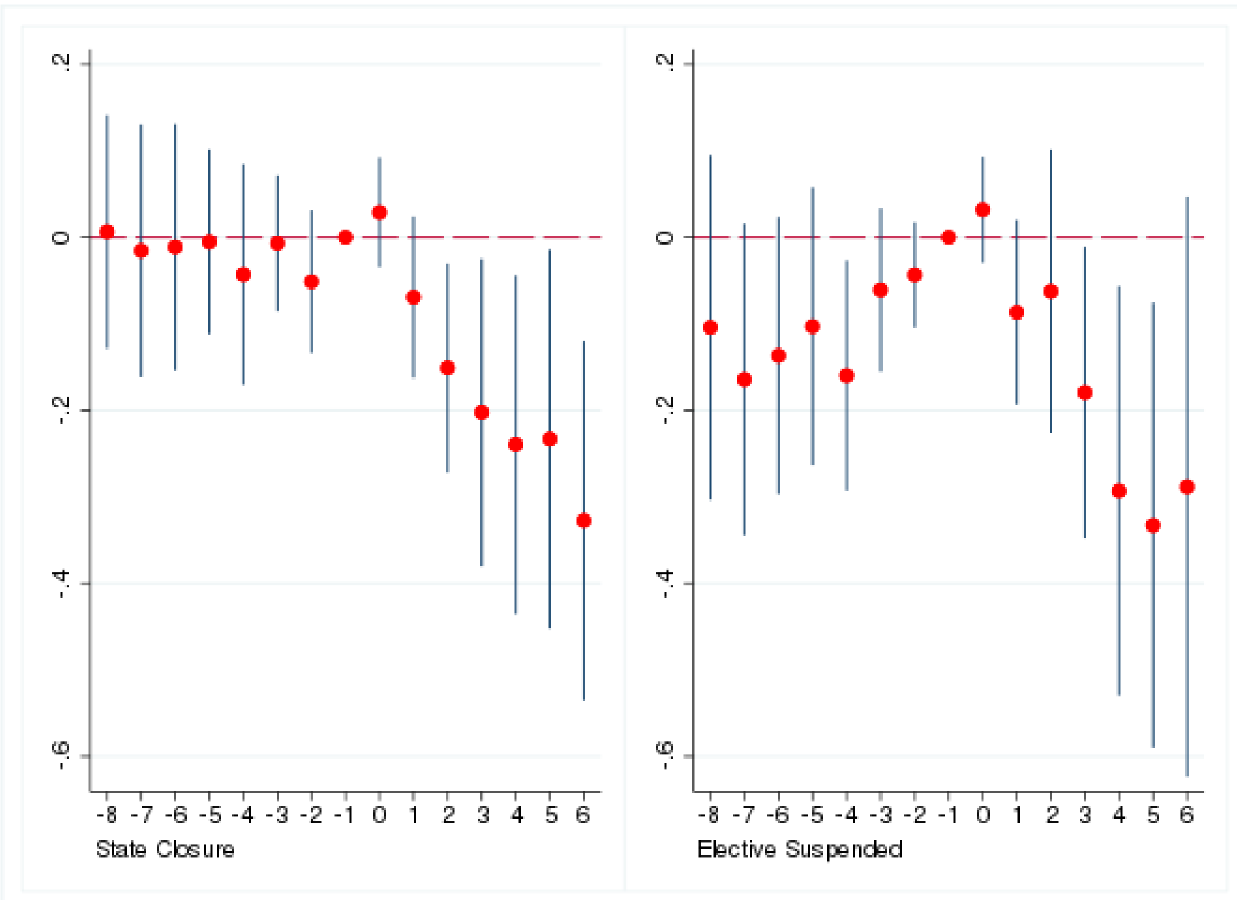
Notes-We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 13: Trends in Weekly Labs/Procedures Between Jan 1st 2019 and May 15th 2020



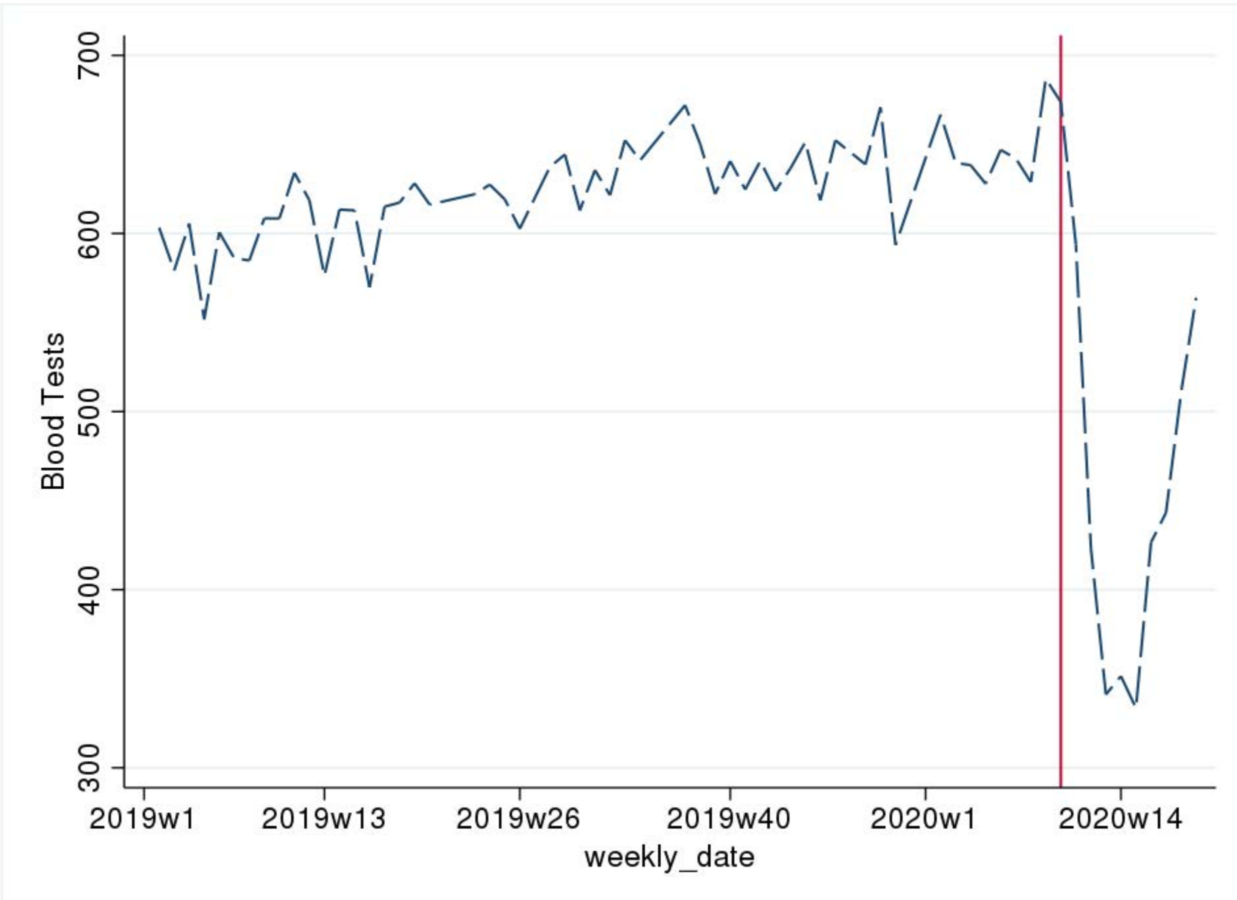
Notes-We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 14: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Total Labs Jan 1st 2019 – May 15th 2020



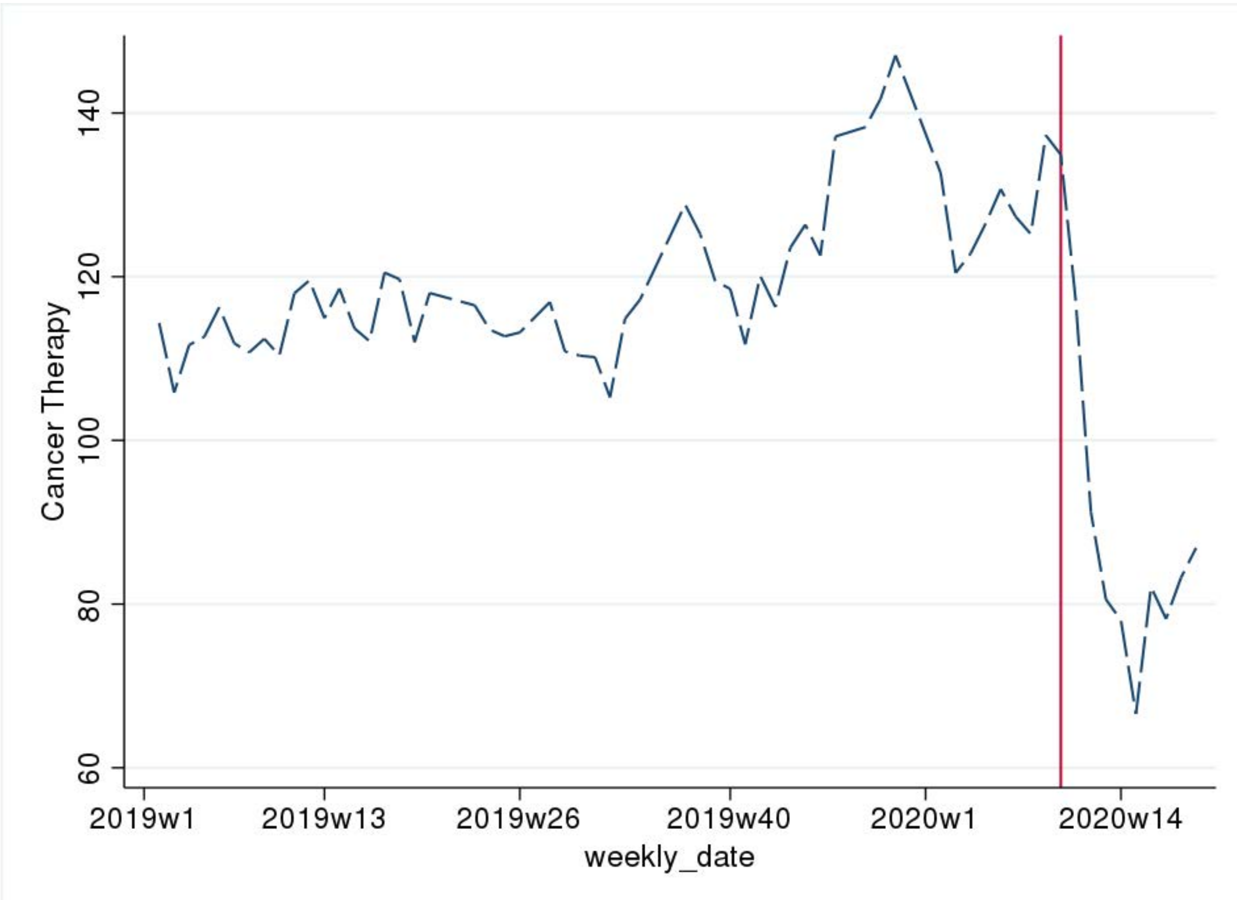
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 15: Trends in Weekly Blood Tests Between Jan 1st 2019 and May 15th 2020



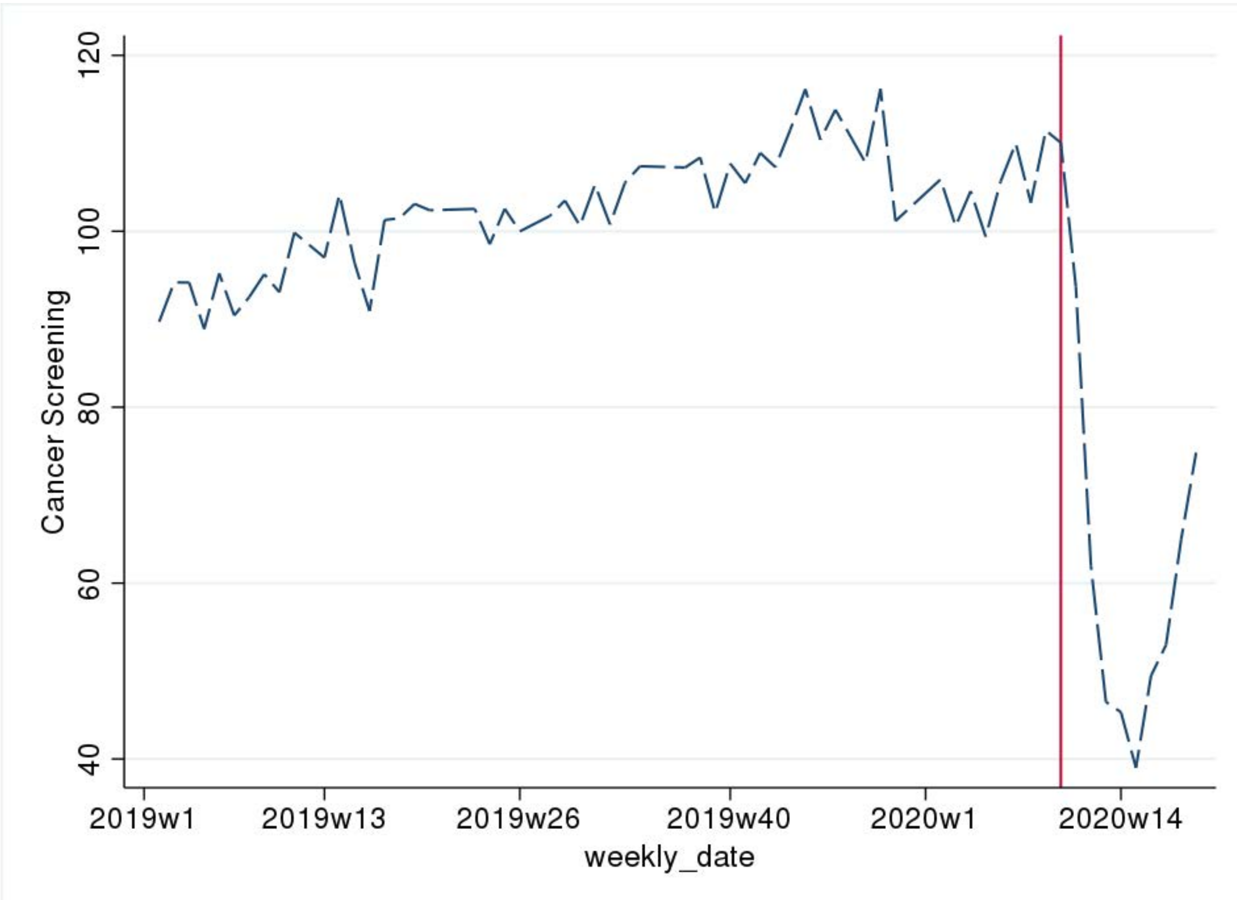
Notes - We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 16: Trends in Weekly Cancer Therapy Between Jan 1st 2019 and May 15th 2020



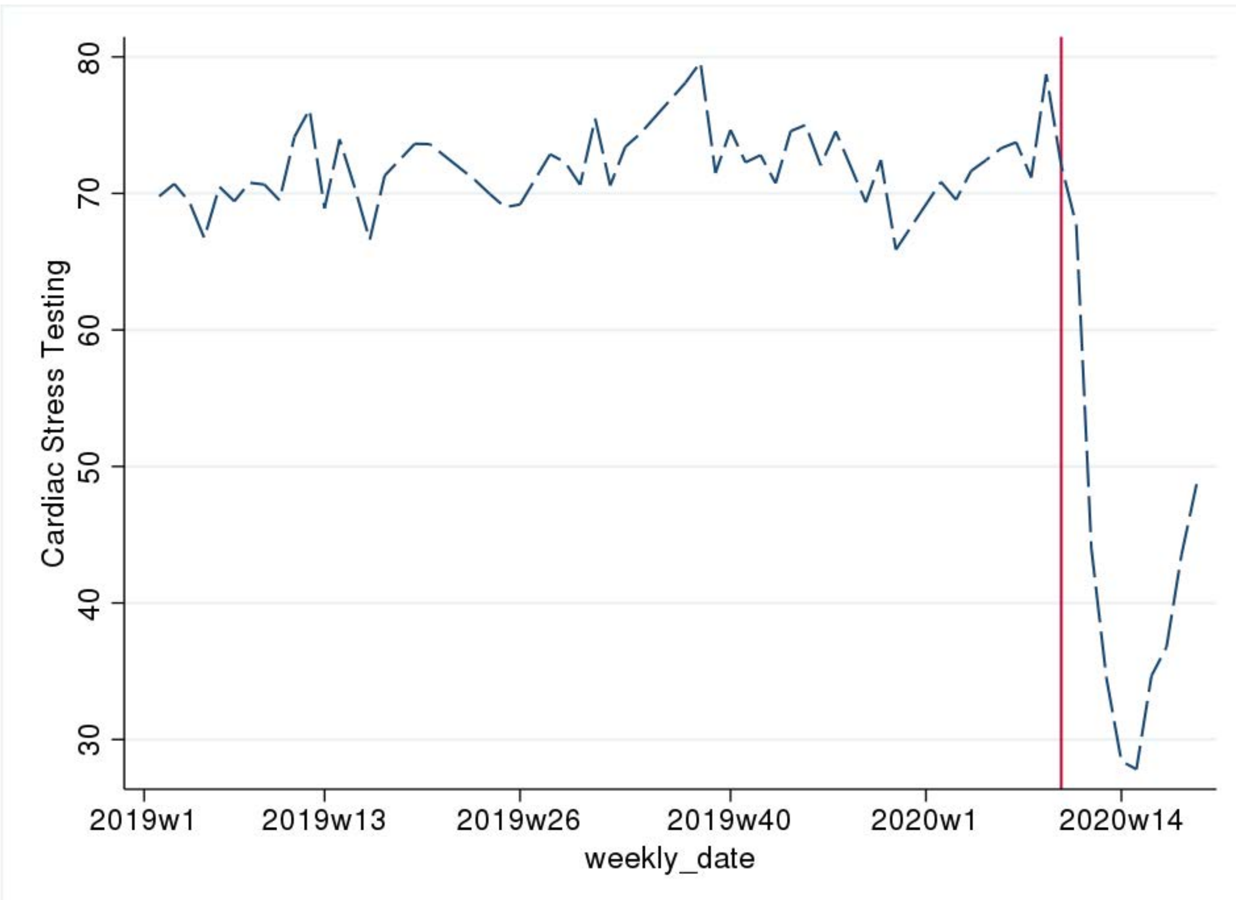
Notes - We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 17: Trends in Weekly Cancer Screenings Between Jan 1st 2019 and May 15th 2020



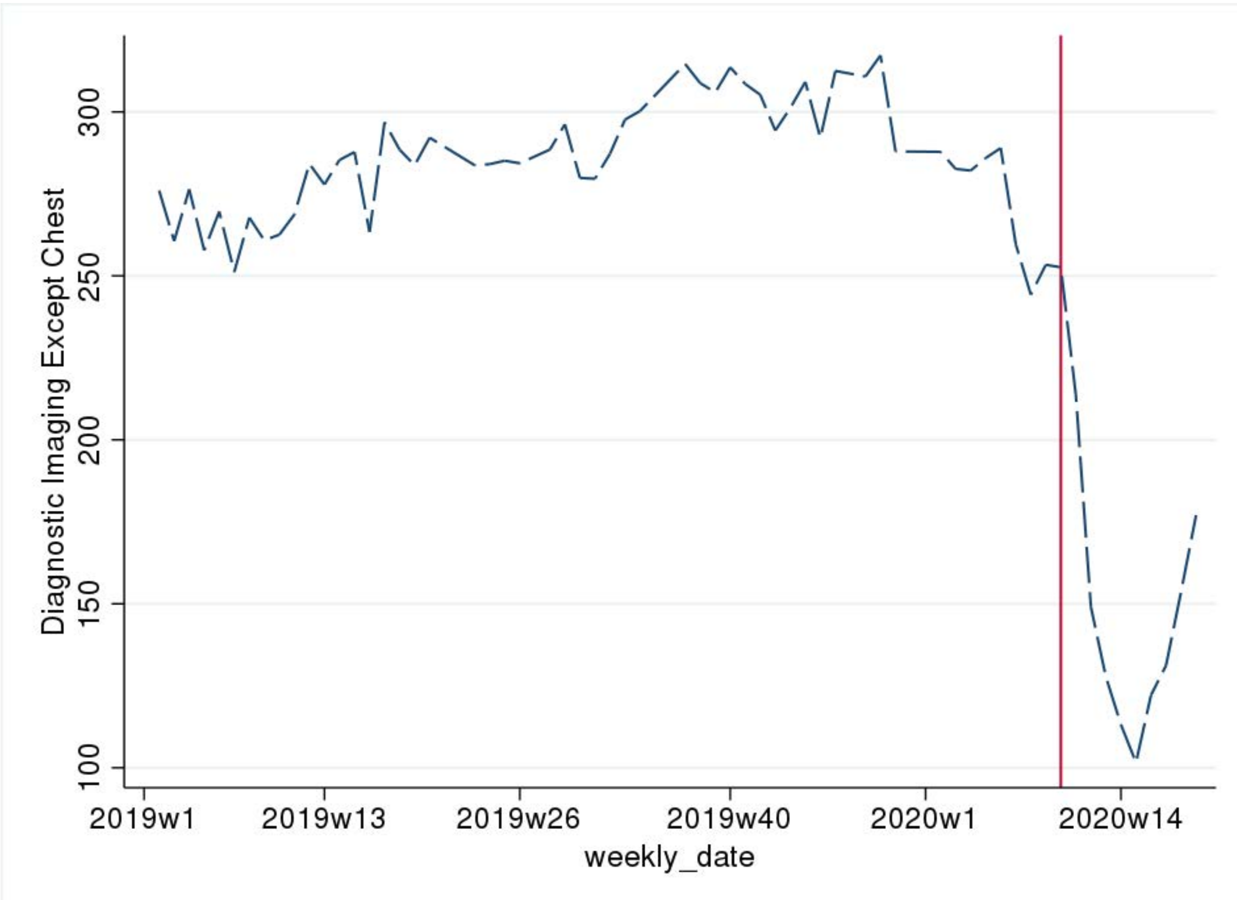
Notes - We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 18: Trends in Weekly Cardiac Stress Testing Between Jan 1st 2019 and May 15th 2020



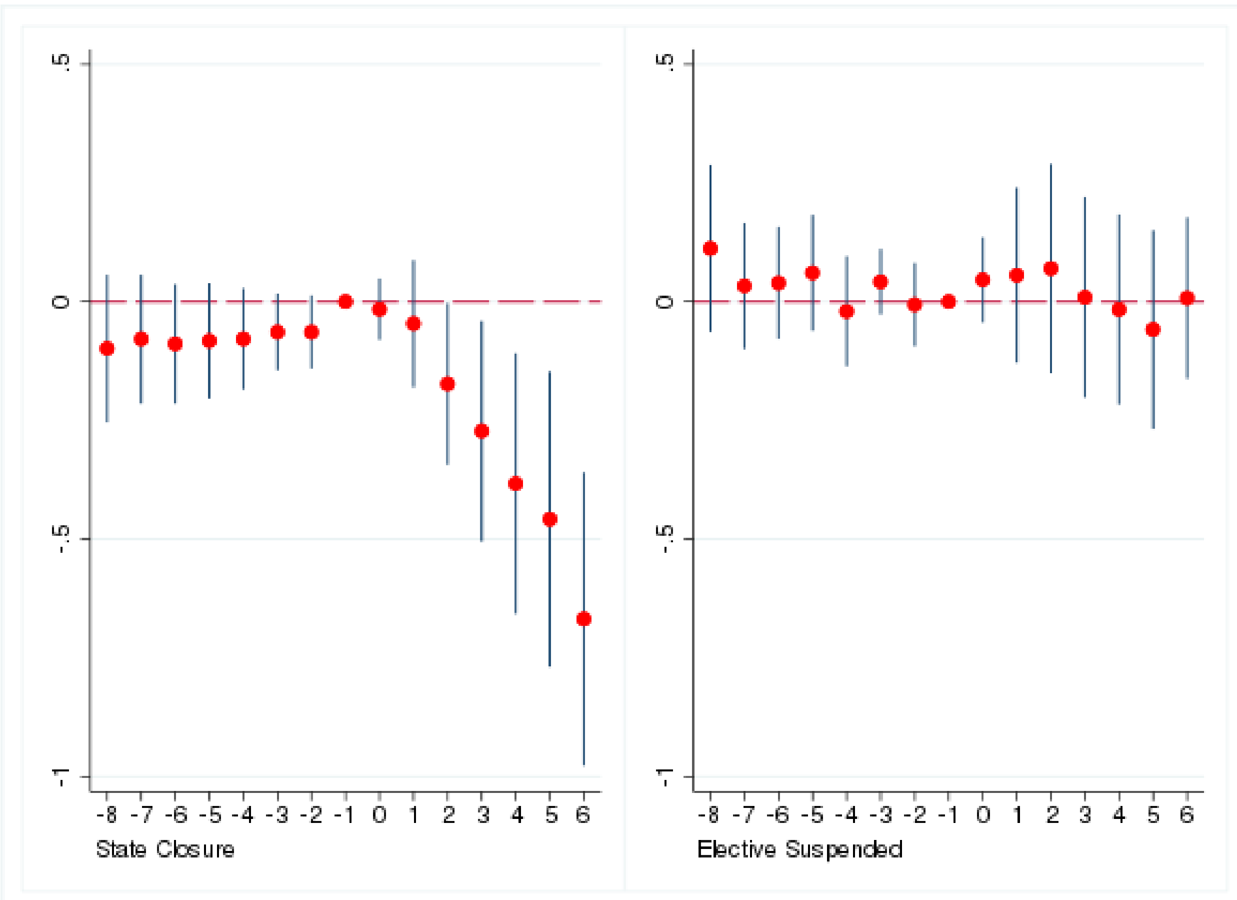
Notes - We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 19: Trends in Weekly Diagnostic Imaging Between Jan 1st 2019 and May 15th 2020



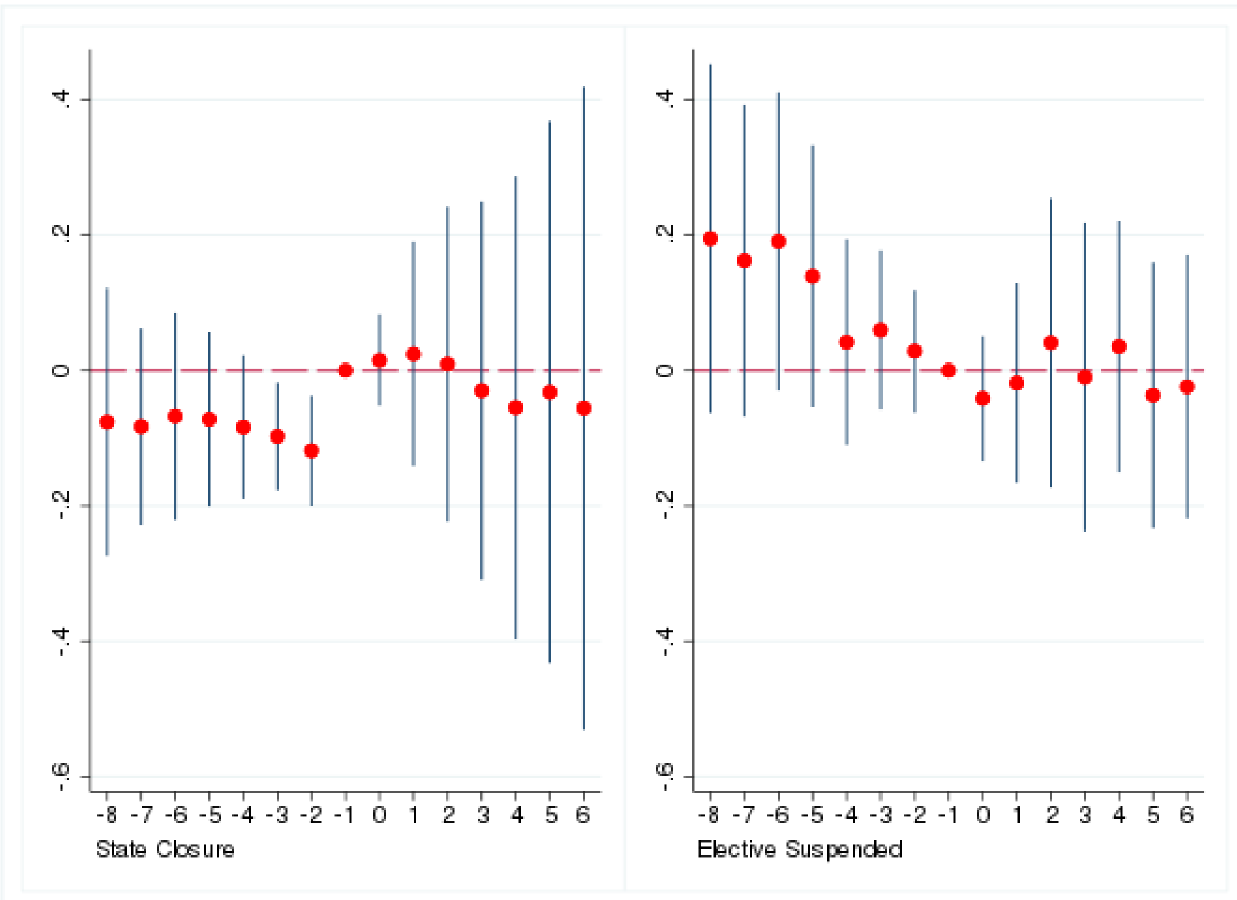
Notes - We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays.

Figure 20: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Blood Tests Jan 1st 2019 – May 15th 2020



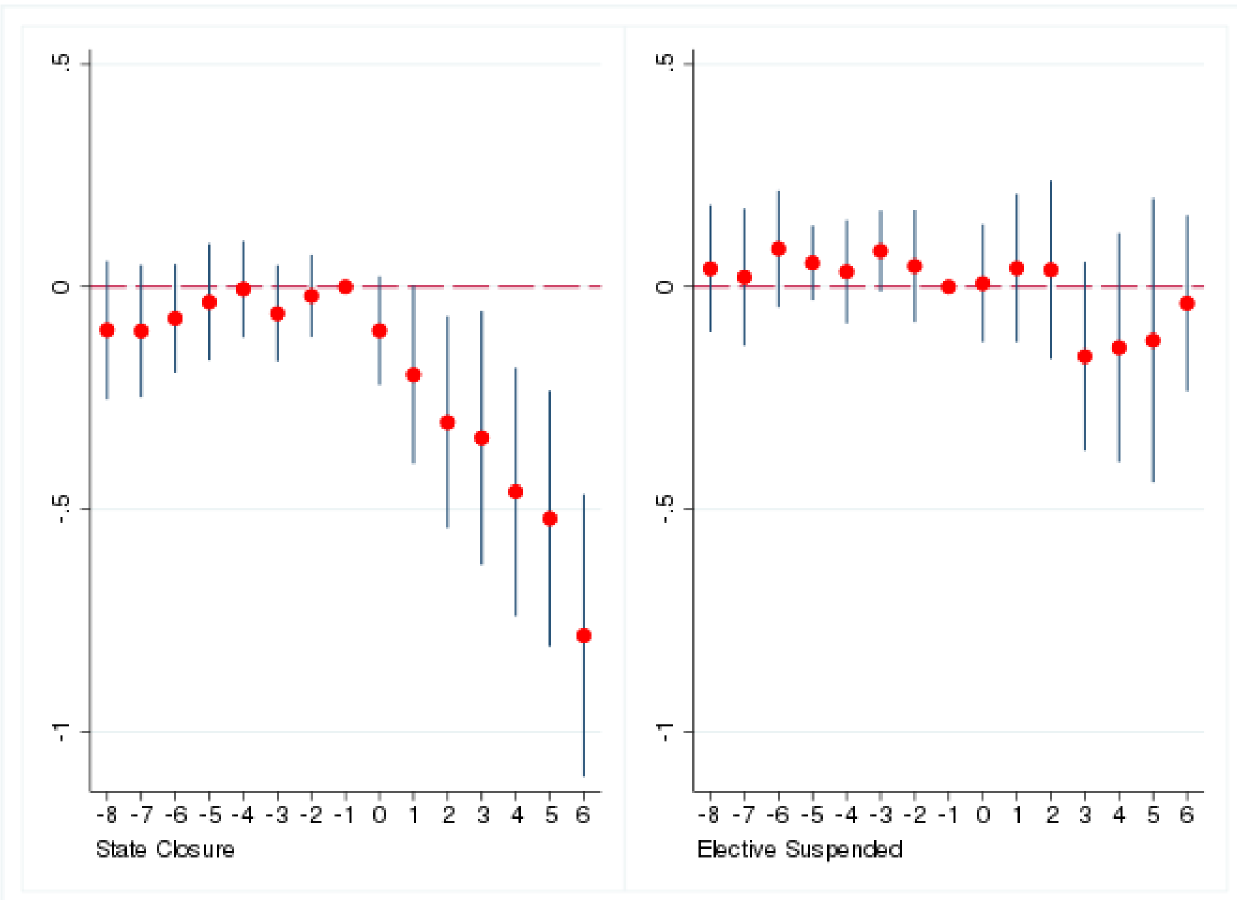
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 21: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Cancer Therapy Jan 1st 2019 – May 15th 2020



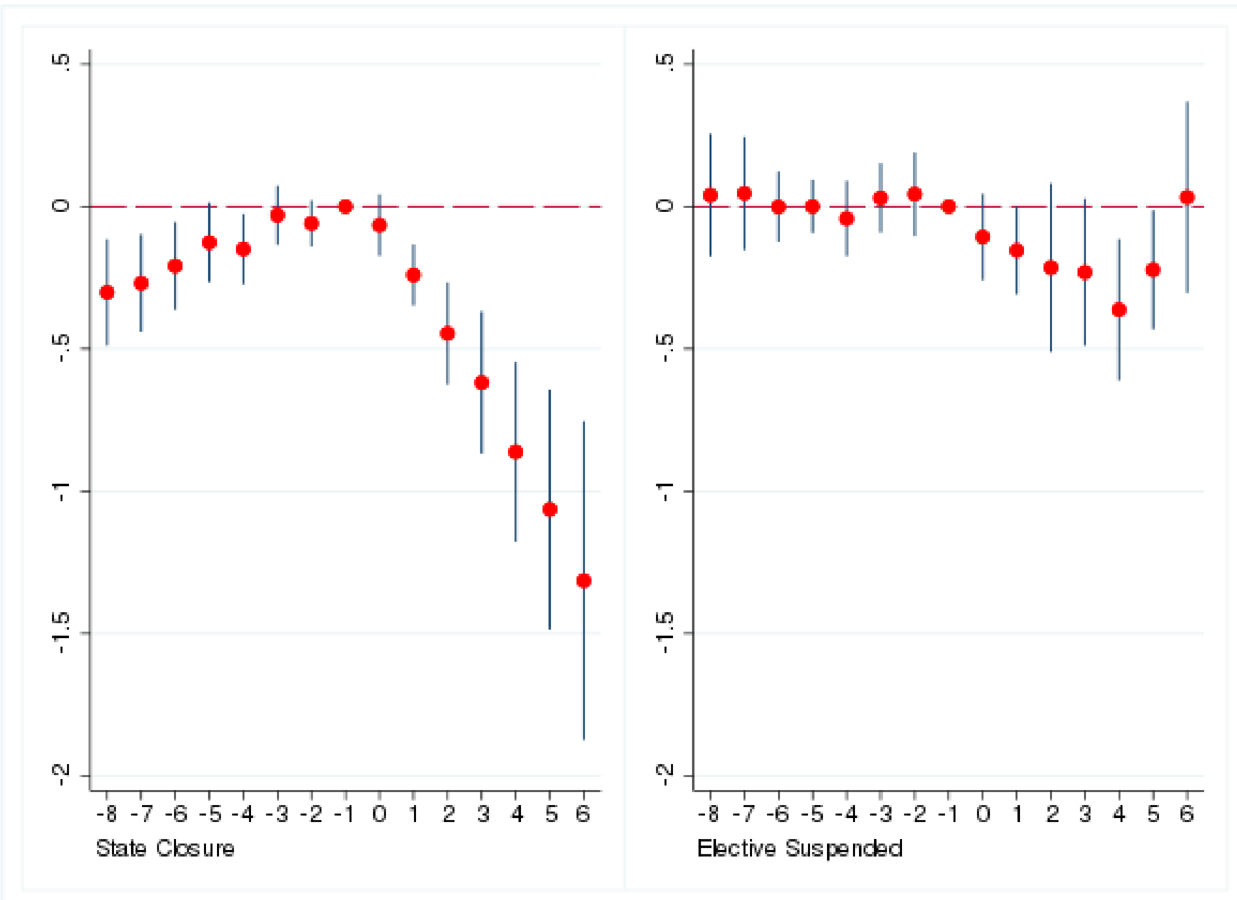
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 22: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Cancer Screenings Jan 1st 2019 – May 15th 2020



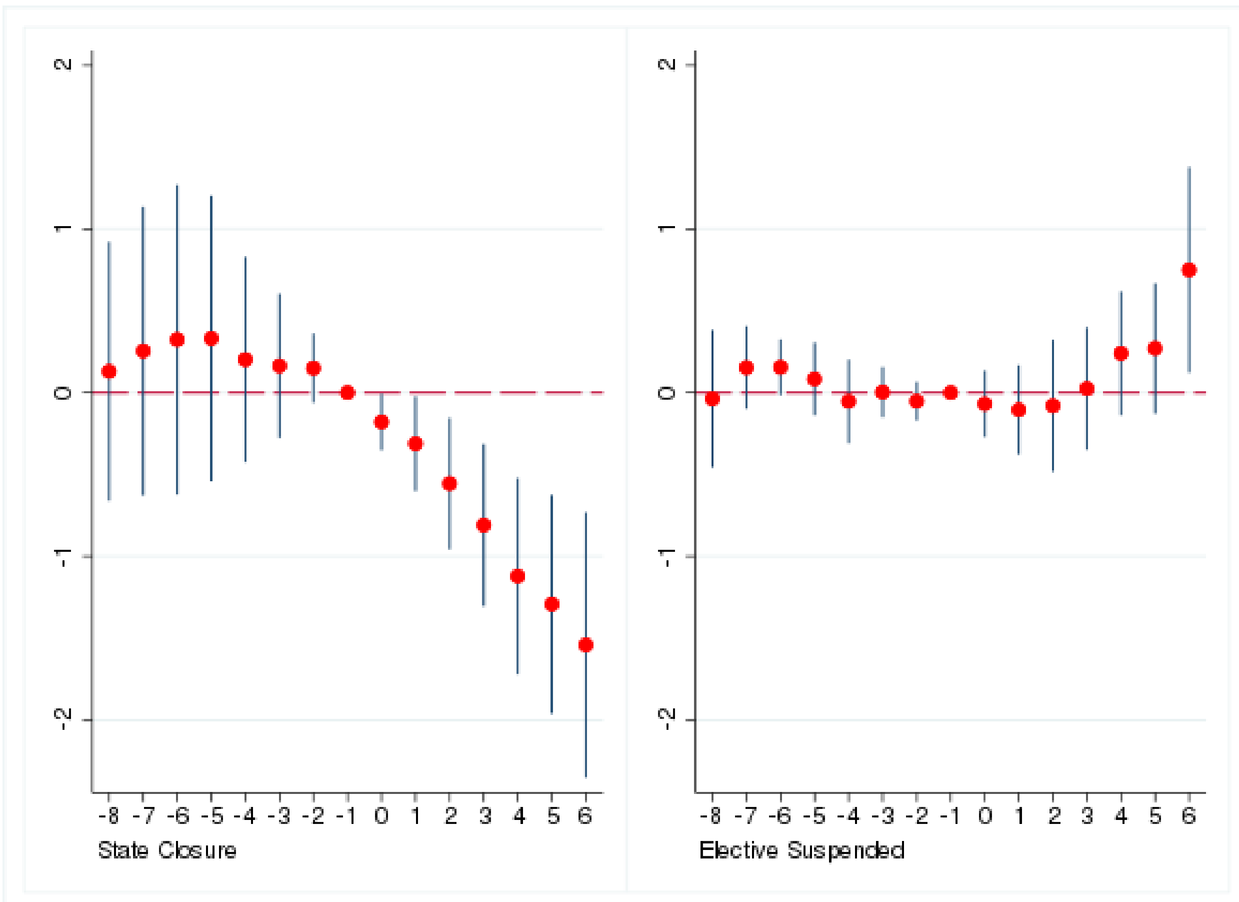
Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 23: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Cardiac Stress Testing Jan 1st 2019 – May 15th 2020



Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

Figure 24: Event Study Coefficients of the Effect of State Closure and Elective Medical Care Suspended on Diagnostic Imaging (Except Chest) Jan 1st 2019 – May 15th 2020



Notes - The unit of observation is the state - calendar week. Regressions include state fixed effects, date fixed effects, indicators for the calendar weeks since state closure occurred (up to eight lags and six post periods) and indicators for the calendar weeks since elective medical procedures were suspended (up to eight lags and six post periods). Standard errors were constructed allowing for non-independence (clustering) within state.

A Appendix

Table A.1: Enacted/Legalized State Policies and State Orders

State	Stay at Home	NEB Closure	Stay at Home Removed or NEB Reopen	Elective Medical Care Suspended	Elective Medical Care Resume	Expanded Malpractice Liability Waivers for Physicians+
AK	28-Mar-20	28-Mar-20	24-Apr-20	Mar-19-20	20-Apr-20	
AL	4-Apr-20		30-Apr-20	Mar-19-20	30-Apr-20	May-8-2020
AR			4-May-20	Apr-3-20	27-Apr-20	Apr-13-2020
AZ	31-Mar-20		8-May-20	Mar-21-20	1-May-20	Apr-9-2020
CA	19-Mar-20	19-Mar-20	8-May-20	Mar-19-20	22-Apr-20	
CO	26-Mar-20	26-Mar-20	1-May-20	Mar-19-20	27-Apr-20	
CT	23-Mar-20	23-Mar-20	20-May-20			Apr-5-2020
DC	1-Apr-20	25-Mar-20	29-May-20			
DE	24-Mar-20	24-Mar-20	1-Jun-20			
FL	3-Apr-20		4-May-20	Mar-20-20	8-May-20	
GA	3-Apr-20		24-Apr-20		20-Apr-20*	Apri-14-2020
HI	25-Mar-20	25-Mar-20	7-May-20	April-16-20	26-Apr-20	
IA			1-May-20	Mar-26-20	27-Apr-20	
ID	25-Mar-20	25-Mar-20	1-May-20			
IL	21-Mar-20	21-Mar-20	1-May-20	Mar-19-20	11-May-20	Apri-1-2020
IN	25-Mar-20	25-Mar-20	4-May-20	Mar-16-20	27-Apr-20	
KS	30-Mar-20		4-May-20			
KY	26-Mar-20	26-Mar-20	11-May-20	Mar-23-20	6-May-20	Mar-30-2020
LA	23-Mar-20	23-Mar-20	15-May-20	Mar-21-20	27-Apr-20	Mar-21-2020
MA	24-Mar-20	24-Mar-20	18-May-20	Mar-15-20	18-May-20	
MD	30-Mar-20	23-Mar-20	15-May-20	Mar-23-20	7-May-20	
ME	1-Apr-20	25-Mar-20	1-May-20	Mar-15-2020	1-May-20	
MI	24-Mar-20	23-Mar-20	7-May-20	Mar-21-20	29-May-20	
MN	28-Mar-20		27-Apr-20	Mar-19-20	10-May-20	
MO	6-Apr-20		4-May-20			
MS	3-Apr-20	3-Apr-20	27-Apr-20	Mar-19-20	24-Apr-20	Mar-14-2020
MT	28-Mar-20	28-Mar-20	26-Apr-20			
NC	30-Mar-20	30-Mar-20	8-May-20	Mar-20-20		
ND			1-May-20			
NE			4-May-20	Apr-3-20	4-May-20	
NH	28-Mar-20	28-Mar-20	4-May-20			
NJ	21-Mar-20	21-Mar-20	2-May-20	Mar-23-20	26-May-20	Apr-14-2020
NM	24-Mar-20	24-Mar-20	1-May-20	Mar-24-20	30-Apr-20	
NV	31-Mar-20		9-May-20			
NY	22-Mar-20	22-Mar-20	15-May-20	Mar-16-20		Mar-23-2020
OH	24-Mar-20	24-Mar-20	1-May-20	Mar-17-20	1-May-20	
OK		1-Apr-20	24-Apr-20	Mar-24-20	24-Apr-20	May-12-2020
OR	23-Mar-20		15-May-20	Mar-19-20	1-May-20	
PA	1-Apr-20	23-Mar-20	8-May-20	Mar-19-20	27-Apr-20	
RI	28-Mar-20		9-May-20			
SC	7-Apr-20		20-Apr-20			
SD			1-May-20	Apr-6-20	28-Apr-20	
TN	1-Apr-20	1-Apr-20	27-Apr-20	Mar-23-20	1-May-20	
TX	2-Apr-20		1-May-20	Mar-22-20	21-Apr-20	
UT	27-Mar-20		1-May-20	Mar-23-20	22-Apr-20	Apr-22-2020
VA	30-Mar-20		15-May-20	Mar-25-20	1-May-20	Apr-28-2020
VT	24-Mar-20	25-Mar-20	27-Apr-20	Mar-20-20	4-May-20	Apr-5-2020
WA	23-Mar-20	25-Mar-20	5-May-20	Mar-19-20	29-Apr-20	
WI	25-Mar-20	25-Mar-20	20-Apr-20			Apr-14-2020
WV	24-Mar-20	24-Mar-20	4-May-20	Mar-31-20	20-Apr-20	
WY		20-Mar-20	1-May-20			

Notes- *Georgia did not order physicians to suspend elective non-urgent care but only recommended it in a press release. + Some of the liability waivers were passed with the emergency declaration others were enacted when the state suspended medical procedures or after the state suspended medical procedures.

Table A.2: Effect of State Policy on Weekly Total Visits and Weekly Total Labs Using Specifications With and Without State Linear Trends

	(1)	(2)
All Weekly Visits		
State Closure	-0.128**	-0.168**
	(0.041)	(0.058)
Elective Medical Suspended	0.075	-0.04
	(0.1)	(0.074)
Added Liability Waivers	-0.119	-0.043
	(0.082)	(0.044)
State Reopen	0.053	0.033
	(0.079)	(0.065)
Elective Medical Reopen	-0.045	0.06
	(0.112)	(0.058)
All Weekly Labs		
State Closure	-0.331**	-0.336**
	(0.0708)	(0.0647)
Elective Medical Suspended	0.046	-0.067
	(0.091)	(0.0732)
Added Liability Waivers	-0.372**	-0.364**
	(0.1306)	(0.1156)
State Reopen	0.01	0.075+
	(0.0577)	(0.0446)
Elective Medical Reopen	0.151	0.170+
	(0.1139)	(0.0914)
State Linear Trends	No	Yes
Observations	2046	2046

The unit of observation is the state- week level. For each outcome variable we present three models. Model 1 includes the state policy variables and state fixed effects, and date fixed effects. Model 2, adds the state linear trends. We use records from Jan 1 2019 to May 15 2020. We exclude patient records from EMR systems not in the data in both 2019 and 2020, and providers not in the data in both 2019 and 2020. We further restrict our analysis to the 31 states with at least 100,000 visits; we also remove visits that are COVID-19 related, and visits on weekends and special holidays. All regressions include state fixed effects, date fixed effect and state linear year trend. Standard errors have been constructed allowing for non-independence of observations within a state. + p-value <0.1, * 0.05 < p-value<=0.01, ** p <= 0.01

References

Akbarpour, M., Cook, C., Marzuoli, A., Mongey, S., Nagaraj, A., Saccarola, M., Tebaldi, P., Vasserman, S., and Yang, H. (2020). Socioeconomic network heterogeneity and pandemic policy response. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-75).

Atasoy, H., Greenwood, B. N., and McCullough, J. S. (2019). The digitization of patient care: A review of the effects of electronic health records on health care quality and utilization. *Annual review of public health*, 40:487–500.

Bhatt, A. S., Moscone, A., McElrath, E. E., Varshney, A. S., Claggett, B. L., Bhatt, D. L., Januzzi, J. L., Butler, J., Adler, D. S., Solomon, S. D., and Vaduganathan, M. (2020). Fewer Hospitalizations for Acute Cardiovascular Conditions During the COVID-19 Pandemic. *Journal of the American College of Cardiology*, 76(3):280–288.

Brunner, J., Rose, D. E., Chuang, E., Canelo, I., and Yano, E. M. (2020). The role of healthcare system hassles in delaying or forgoing care. In *Healthcare*, page 100411. Elsevier.

Calvo-Alén, J. (2010). Opioids in chronic musculoskeletal conditions. *Therapeutic advances in musculoskeletal disease*, 2(5):291–297.

Cronin, C. J. and Evans, W. N. (2020). Private precaution and public restrictions: What drives social distancing and industry foot traffic in the covid-19 era? Technical report, National Bureau of Economic Research.

De Filippo, O., D'Ascenzo, F., Angelini, F., Bocchino, P. P., Conrotto, F., Saglietto, A., Secco, G. G., Campo, G., Gallone, G., Verardi, R., Gaido, L., Iannaccone, M., Galvani, M., Ugo, F., Barbero, U., Infantino, V., Olivotti, L., Mennuni, M., Gili, S., Infusino, F., Vercellino, M., Zucchetti, O., Casella, G., Giammaria, M., Boccuzzi, G., Tolomeo, P., Doronzo, B., Senatore, G., Grosso Marra, W., Rognoni, A., Trabattoni, D., Franchin, L., Borin, A., Bruno, F., Galluzzo, A., Gambino, A., Nicolino, A., Truffa Giachet, A., Sardella, G., Fedele, F., Monticone, S., Montefusco, A., Omedè, P., Pennone, M., Patti, G., Mancone, M., and De Ferrari, G. M. (2020). Reduced Rate of Hospital Admissions for ACS during Covid-19 Outbreak in Northern Italy. *The New England Journal of Medicine*, 383(1):88–89.

Doyle, J. J. (2011). Returns to local-area health care spending: evidence from health shocks to patients far from home. *American Economic Journal: Applied Economics*, 3(3):221–43.

Doyle, J. J., Graves, J. A., Gruber, J., and Kleiner, S. A. (2015). Measuring returns to hospital care: Evidence from ambulance referral patterns. *Journal of Political Economy*, 123(1):170–214.

Fisher, E. S., Wennberg, D. E., Stukel, T. A., Gottlieb, D. J., Lucas, F. L., and Pinder, E. L. (2003). The implications of regional variations in medicare spending. part 1: the content, quality, and accessibility of care. *Annals of internal medicine*, 138(4):273–287.

Frakes, M. (2013). The impact of medical liability standards on regional variations in physician behavior: Evidence from the adoption of national-standard rules. *American Economic Review*, 103(1):257–76.

Frakes, M. and Gruber, J. (2019). Defensive medicine: Evidence from military immunity. *American Economic Journal: Economic Policy*, 11(3):197–231.

Garcia, S., Albaghdadi, M. S., Meraj, P. M., Schmidt, C., Garberich, R., Jaffer, F. A., Dixon, S., Rade, J. J., Tannenbaum, M., Chambers, J., Huang, P. P., and Henry, T. D. (2020). Reduction in ST-Segment Elevation Cardiac Catheterization Laboratory Activations in the United States During COVID-19 Pandemic. *Journal of the American College of Cardiology*, 75(22):2871–2872.

Goolsbee, A. and Syverson, C. (2020). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. Working Paper 27432, National Bureau of Economic Research.

Gupta, S., Nguyen, T. D., Rojas, F. L., Raman, S., Lee, B., Bento, A., Simon, K. I., and Wing, C. (2020a). Tracking public and private response to the covid-19 epidemic: Evidence from state and local government actions. Technical report, National Bureau of Economic Research.

Gupta, S., Simon, K., and Wing, C. (2020b). Mandated and voluntary social distancing during the covid-19 epidemic. In *Brookings Papers on Economic Activity*, volume 25.

Hartnett, K. P. (2020). Impact of the COVID-19 Pandemic on Emergency Department Visits — United States, January 1, 2019–May 30, 2020. *MMWR. Morbidity and Mortality Weekly Report*, 69.

Krumholz, H. (2020). Where have all the heart attacks gone. *New York Times*, 6.

Mehrotra, A. et al. (2020). The impact of the covid-19 pandemic on outpatient visits: A rebound emerges. *To the Point*.

Mello, M. M., Frakes, M. D., Blumenkranz, E., and Studdert, D. M. (2020). Malpractice liability and health care quality: a review. *Jama*, 323(4):352–366.

Montvida, O., Dibato, J. E., and Paul, S. (2020). Evaluating the representativeness of us centricity electronic medical records with reports from the centers for disease control and prevention: Comparative study on office visits and cardiometabolic conditions. *JMIR Medical Informatics*, 8(6):e17174.

Murray, C. J., Abraham, J., Ali, M. K., Alvarado, M., Atkinson, C., Baddour, L. M., Bartels, D. H., Benjamin, E. J., Bhalla, K., Birbeck, G., et al. (2013). The state of us health, 1990-2010: burden of diseases, injuries, and risk factors. *Jama*, 310(6):591–606.

Rosenbaum, L. (2020). The Untold Toll — The Pandemic's Effects on Patients without Covid-19. *New England Journal of Medicine*, 382(24):2368–2371.

Sarac, N. J., Sarac, B. A., Schoenbrunner, A. R., Janis, J. E., Harrison, R. K., Phieffer, L. S., Quatman, C. E., and Ly, T. V. (2020). A Review of State Guidelines for Elective Orthopaedic Procedures During the COVID-19 Outbreak. *The Journal of Bone and Joint Surgery. American Volume.*

Sheth, K. (2020). Hospital admissions for strokes appear to have plummeted, a doctor says, a possible sign people are afraid to seek critical help. *Washington Post. April*, 9.

Verma, S. (2020). Early impact of cms expansion of medicare telehealth during covid-19.

Vordermark, D. (2020). Shift in indications for radiotherapy during the covid-19 pandemic? a review of organ-specific cancer management recommendations from multidisciplinary and surgical expert groups. *Radiation Oncology*, 15(1):1–4.

Weissman, J. S., Stern, R., Fielding, S. L., and Epstein, A. M. (1991). Delayed access to health care: risk factors, reasons, and consequences.

Williamson, E. J., Walker, A. J., Bhaskaran, K., Bacon, S., Bates, C., Morton, C. E., Curtis, H. J., Mehrkar, A., Evans, D., Inglesby, P., et al. (2020). Opensafely: factors associated with covid-19 death in 17 million patients. *Nature*, pages 1–11.