Working Paper

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Online Physician Transformations During COVID-19

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RAND Health Care

WR-A621-5
January 2021

RAND
CORPORATION

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Published by the RAND Corporation, Santa Monica, Calif.

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ABSTRACT

For a variety of firms, interactions with consumers can be conducted through in-person or virtual means, but how firms select different mediums is unclear. We examine this question using the market for almost all physician groups in the United States and their adoption of a telemedicine platform during the COVID-19 pandemic. We link detailed data on physician use of the telemedicine platform with mobility data from global positioning services (GPS) tracking services. Our combined data allows us to quantify physician-level substitution between in-person interactions with patients and virtual interactions. As a source of identifying variation, we leverage differential county-level exposure to the COVID-19 pandemic and related social distancing policies. Consistent with existing work, our first stage and reduced form results show large reductions in in-person visits and increases in use of telemedicine. Our instrumented results show an elasticity of approximately -0.2 between in-person and virtual care for all physicians located in the United States and an elasticity ranging from -1.0 to -0.3 for physicians who are regular users of the platform. Our results highlight how physician firms strategically adopt telemedicine in response to reductions in in-person demand for services.

* RAND Corporation, Santa Monica, CA. Cantor, jcantor@rand.org; Whaley, cwhaley@rand.org. Funding provided by NIA K01AG061274. We thank Doximity and SafeGraph for access to the data used in this study, Matt Eisenberg, Thuy Nguyen, David Powell, and discussants at the 2020 CHITA Conference. This project was approved by the RAND Human Subjects Protection Committee.

1. INTRODUCTION

How do firms interact with customers? Technological innovations, including digitization, have enabled several modes of customer interaction. Due to these technological advancements a variety of firms can now engage with consumers through in-person or virtual means. However, the mechanism by which a firm selects the medium to engage with consumers is unclear. Previous literature has indicated that digital markets lead to new platforms for two main reasons (Jullien 2012). First, a digital platform facilitates matching via low search costs, creating efficient matches and network externalities (Goldfarb and Tucker 2019). Second, digital platforms allow firms to reach a large number of customers quickly, and firms can adjust the platform at a low cost (Hagiu 2012).

Both of these components are particularly important within the context of health care, but the effect of digitization on health care firms is not well understood. Understanding the shift to digital platforms is also critical within the context of the COVID-19 pandemic, given that the Centers for Disease Control and Prevention has recommended against in-person office visits (Centers for Disease Control and Prevention 2020). In this paper, we examine how firms adopt technologies using the market for physicians in the United States during the COVID-19 pandemic. Traditionally, the vast majority of physician care is delivered in-person, even though many telemedicine technologies that allow physicians to provide care for patients through telemedicine services have been developed over the last decade. Existing research has found the use of telemedicine services is low (Barnett et al. 2018). Why these services have experienced relatively low growth remains an open question. Common reasons include the cost of implementation (Zachrison et al. 2020; Scott Kruse et al. 2018), variable and insufficient reimbursement (Uscher-Pines, Sousa, Palimaru, et al. 2020; Scott Kruse et al. 2018), onerous government policy (Goodman and Brett 2020; Lee, Karsten, and Roberts 2020), a lack of training (Edirippulige and Armfield 2017; Scott Kruse et al. 2018), and concerns on quality of care provided via digital platforms (Uscher-Pines 2020; Uscher-Pines, Huskamp, and Mehrotra 2020).

However, the COVID-19 pandemic has greatly expanded the use of telemedicine services for several reasons. First, the CDC has recommended that patients and physicians interact via digital platforms whenever possible as opposed to through in-office visits (CDC 2020). Second, state-level social distancing policies encourage patients to not leave their household and force the patient and physician to interact remotely (Koonin 2020). In previous work, we found that patient use of telehealth services increased by over 1,000 percent in the initial month of the COVID-19 pandemic (Whaley et al. 2020). Other studies have found a large increase in the use of telehealth services during the COVID-19 pandemic (Schneider and Shah 2020; Ziedan, Simon, and Wing 2020; Lau et al. 2020; Baum, Kaboli, and Schwartz 2020; Koonin 2020; Verma 2020; Cantor et al. 2020), and increased access to telemedicine services is an important policy goal during the pandemic (Jordan 2020).

While telemedicine utilization rates have been explored (Barnett et al. 2018; Koonin 2020), the mechanisms by which physicians adopt telemedicine has received less attention. In this paper, we examine how firms, in this case physicians, adopt a new technology—telemedicine. To do so, we combined detailed data on physician use of a particular telemedicine platform with mobility data from global positioning services (GPS) tracking services that is linked to individual physician locations. The Doximity telemedicine tool, described in more detail below, is a freely-available tool for physicians and other licensed health care providers to virtually communicate with patients compliant with privacy regulations. Our combined data allows us to quantify physician-level substitution between in-person interactions with patients and virtual interactions.

The change in both in-person and telemedicine visits over our study period is striking. As shown in Figure 1, following the U.S. emergency declaration for the COVID-19 pandemic, the aggregate weekly number of in-person visits to physician offices in our data decreased by approximately 8 million, approximately a 50 percent decline. The number of telemedicine calls through the platform we study increased by approximately 3 million calls per week, an over 1,200 percent increase.

To measure the causal effect of substitution between in-person care and telemedicine, we leverage geographic variation in both social distancing policies, which limit mobility, and variations in the intensity of the COVID-19 pandemic across markets. This approach raises a number of empirical challenges inherent to estimating the effects of the COVID-19 pandemic (Goodman-Bacon and Marcus 2020). To ensure the validity of our results, we non-parametrically control for the diffusion of the COVID-19 pandemic across markets. We also estimate a sensitivity test that estimates changes in telemedicine adoption in response to market-wide, rather than firm-level, changes in demand, under the assumption that providers should be more responsive to changes in their own demand, rather than market-level demand.

Consistent with existing work, our first stage and reduced form results show reductions in in-person visits and increases in the use of telemedicine. For example, after adjusting for local-market variations in exposure to the COVID-19 pandemic, the county-level implementation of social distancing policies leads to a 4.1 percent reduction in within-physician weekly foot-traffic to the physician's office and a 1.5 percent increase in within-physician telemedicine calls. When linking these two changes, we estimate a substitution elasticity between use of telemedicine and in-person patient demand of approximately -0.2 for all U.S. physicians, and ranging from -1.0 to -0.3, depending on the specification, for active users of the telemedicine platform we study.

Our paper makes three main contributions. First, our paper contributes to the literature on how firms adopt technologies. While several studies have documented the effects of technology adoption on firm performance (e.g., Brown and Goolsbee 2002; Ater and Orlov 2014; Akerman, Gaarder, and Mogstad 2015), few studies have documented *why* firms adopt new technologies. While eventually productivity enhancing, implementing new technology involves transaction costs and, in many settings, leads to heterogeneity in firm adoption (Saloner and Shepard 1995). Other studies have examined technology adoption for steel manufactures, banking, and CD players (Oster 1982; Hannan and McDowell 1984; Gandal, Kende, and Rob 2000). Related work finds federal subsidies led to the adoption of electronic health records for hospitals (Dranove et al. 2015), and state privacy regulations slow the adoption of electronic medical records (Miller and Tucker 2009). However, the existing literature has not considered similar types of technological innovation for a market with as many firms as the U.S. physician market. The existing literature has also not considered firm technology adoption during an acute shock to patient demand as large as the COVID-19 pandemic.

Relatedly, our second contribution is that the results contain policy-relevant information on how patient-physician interactions have changed during the COVID-19 pandemic. While several studies have documented the rise in patient-use of telemedicine services during the COVID-19 pandemic (Mann et al. 2020; Chunara et al. 2020; Koonin 2020), the provider side of the market remains understudied, with a focus on qualitative work (Uscher-Pines, Sousa, Raja, et al. 2020). We provide detailed evidence on how physicians use telemedicine in response to shocks to consumer demand. Specifically, our results can inform whether the use of telemedicine is primarily due to county-level shelter in place (SIP) policy or instead caused by the presence of COVID-19 cases and deaths within a county. The size of the effect on telemedicine use due to a SIP policy is likely related to the number of COVID-19 cases and deaths (Cantor et al. 2020). Therefore, our results will be a more accurate representation of how physicians responded to the pandemic and can assist policymakers in tailoring future interventions related to telemedicine in the absence of a pandemic.

Finally, our paper leverages unique data and approaches to analyze types of data that are becoming increasingly common. Our first source of data, mobility-based tracking, has been used in several other studies that use similar approaches to examine mobility changes during the COVID-19 pandemic (Allcott et al. 2020; Goolsbee and Syverson 2020; Jay et al. 2020; Andersen, Bryan, and Slusky 2020; Nguyen et al. 2020; Chen, Chevalier, and Long 2020). Our approach is different in that we link this data to individual business locations to track the *within-firm* change in consumer demand. This detailed data, while originally developed and used for marketing purposes, has important implications for economic research. For example, we use this data to describe the impact of social distancing policies on changes in demand for individual firms. These types of data could be likewise leveraged to monitor firm-level demand in response to other policies (e.g., congestion pricing) or economic factors (e.g., business cycles). Several studies have started to do so within the context of COVID-19 (Cronin and Evans 2020; Goolsbee and Syverson 2020). Our second source of data, telemedicine call logs, is similar to data collected by many technology firms. We leverage this data as an indicator of firm behavior for physician practices, but similar types of data (e.g., search data) have implications for other settings.

From an analytic approach, the process of mapping individual firms to the SafeGraph data uses machine learning and natural language processing models. Due to advances in both computing power and model development, these approaches have become widespread, especially among technology firms. Our approach combines these innovative statistical models with traditional econometric approaches to leverage the large-scale data we collect to understand the adoption of the telemedicine platform by physicians and the tradeoff between in-person office visits and the use of the telemedicine platform.

While this paper is focused on a specific sector, physicians, our findings are relevant for many other markets. For example, technology to conduct meetings and seminars online has existed for years, but many professions are just now widely using these technologies.

The rest of the paper is structured as follows. First, we describe the digital software application and outline the multiple data sources and measures used in the present study. Second, we provide an overview of the methods used for examining the adoption and use of the digital software application. Third, we present the results. Finally, we explain how our results can be interpreted within the broader literature on technology adoption and present policy implications for during and beyond the COVID-19 pandemic.

2. DATA

2.1. Doximity Dialer Data

To measure physician-level use of telehealth services, we use detailed micro-data on all telehealth calls conducted through the Doximity Dialer platform. Doximity is an online professional medical network and digital platform for U.S. physicians and other health care providers (e.g., nurse practitioners). More than 70 percent of U.S. physicians, are registered users of the Doximity platform (*Doximity Dialer* 2020). In October 2016, Doximity implemented an application (Dialer) that allows physicians and other health care providers to communicate with patients via their personal cell phone in a HIPAA-compliant environment. Through the application, health care providers can call patients on their smartphone, but patients see a pre-specified number, rather than the physician's personal number. The pre-specified number can be customized to the doctor's office or physician group. In May 2020, video capability was added to the application, which allows health care providers to communicate with patients visually and in a HIPAA-compliant nature.

From Doximity, we obtained physician-level data on the daily volume of calls from October 2016 through August 2020. Physicians are identified by the National Provider Identifier (NPI), which is used by CMS to identify unique U.S. physicians and health care providers. For each physician, we identified whether the physician used the application and their total call volume in each week. We also measured the total calls in each week among physicians who use the call. Specific patient interactions or the content of calls are not recorded or tracked, and we are thus unable to examine questions related to interactions between providers and individual patients. The sample was limited to U.S. physicians.

Previous work has found that use of the platform is associated with increased volume of Medicare patients seen by providers. The program experienced rapid growth over the 2016 to 2020 period. Over this period, 21.3 million total calls were placed on the platform. However, this growth pales in comparison to the rate of growth beginning in March 2020. In the first month of the COVD-19 pandemic, March 2020, 5.5 million patient-physician interactions were conducted through the platform. In April and May 2020, approximately 22 million calls were conducted.

Thus, the monthly call volume exceeded the cumulative volume from over the first three years of the application's availability.

2.2. National Plan and Provider Enumeration System (NPPES) Data

We next use data from the National Plan and Provider Enumeration System (NPPES) system to identify the universe of U.S. health care providers with a valid NPI. The NPPES data contains both professional and facility providers, but we limit the sample to physicians and related health care providers (e.g., nurse practitioners). For this population, the NPPES data contains unique NPIs and also provider locations. We geocode the address of the provider's primary location.

2.3. SafeGraph Location Tracking Data

Finally, we used the anonymized "Weekly Patterns" data from SafeGraph to quantify in office health care utilization. In this dataset, for each weekly file, SafeGraph makes one row for each Point of Interest (POI). POI are individual business listings or geospatial points for locations of business locations. For each POI, SafeGraph reports its geographic location, industry via the National American Industry Classification System (NAICS) code, and the total number of visitors in their mobile device panel that have visited each day. In the case of physician offices, this can be interpreted as the number of mobile devices that visited that office on a particular day. The weekly data measures begin on Monday and end the following Sunday.

We match the geocoded street address of the office for each physician in the NPPES data to SafeGraph's weekly pattern date. To do so, we use SafeGraph's proprietary algorithm to match the location of unique NPIs to a unique POI in the SafeGraph data. The algorithm that SafeGraph uses for linking primarily relies on the name and address to identify locations that are both in the SafeGraph data and the user's data, in this case the information as logged in the NPPES (SafeGraph 2020). We use the SafeGraph identifier that is appended to the NPPES provider data to calculate the total number of weekly visits to each provider from the SafeGraph "Weekly Patterns" data.

2.4. COVID-19 Policies and Exposure Data

To account for differential exposure to the COVID-19 pandemic we accumulated data on county-level shelter in place policies that was collected by Cook et al. (2020). First, the authors collected the dates for statewide orders from the New York Times (The New York Times 2020). Second, for states that lacked a state-wide order, the authors determined whether an individual county had a shelter in place policy by searching local news and government sites. Finally, the counties for which the authors did not find information on a shelter in place policy were assumed to have followed the state's guidance (Cook, Newberger, and Smalling 2020).

However, given that many of these policies were enacted in response to COVID-19 cases and deaths, we also collected data on COVID-19 incidence rates. The data come from USAFacts and have been frequently used by researchers (Cantor et al. 2020; Adhikari et al. 2020; C. S. Brown and Ravallion 2020). The USAFacts data come from the CDC, which collects the number of cases and deaths from state public health websites. The USAFacts data has the total number of cases and deaths in each county for each day. From the data we found the week of the first COVID-19 case and COVID-19 death for each county.

3. ECONOMETRIC APPROACH

With this data, our primary empirical approach is to estimate how changes in patient demand for individual providers lead to substitution towards telehealth technologies. An empirical challenge is the potential endogeneity between patient demand and unobserved characteristics (e.g., provider quality). As a solution, we leverage the differential impact of the COVID-19 pandemic on in-person demand as a source of exogenous variation. This approach has been used previously (Cantor et al. 2020). To do so, we estimate an instrumental variables regression of the form that estimates the impact of changes in demand for in-person care (D) for provider j in market g during week t on use of telehealth services ($telehealth_{jgt}$):

First stage: $\ln(visits)_{jgt} = \alpha + \beta policy_{gt} + \gamma COVID_{gt} + \psi provider_j + \tau week_t + \gamma market_s + \varepsilon_{jgt}$

Second stage: $telehealth_{jgt} = \alpha + \delta \ln(\widehat{visits})_{jgt} + \psi provider_j + \tau week_t + \gamma market_s + \varepsilon_{jgt}$

In this model, the $policy_{gt}$ is a weekly indicator for the implementation of social distancing policies in each local market. We estimate these models using all three of our $telehealth_{jgt}$ outcome variables—the log-transformed number of telehealth calls made in a week, the extensive-margin probability of having any calls, and the intensive-margin log-transformed calls conditional on having any calls.

We include fixed effects for week and county. The week fixed effects are particularly relevant because they capture the nationwide response to the COVID-19 pandemic. Thus, our model estimates the marginal demand response that occurs in each market following implementation of social distancing policies, relative to nationwide demand responses, and after controlling for that market's exposure to the COVID-19 pandemic. We estimate this model using two-stage least squares and cluster standard errors at the county level. We log-transform both weekly in-person foot traffic and telehealth calls to obtain elasticity estimates. We also estimate an analogous reduced form regression that estimates the impact of social distancing policies on use of telehealth services:

Reduced form: $telehealth_{jgt} = \alpha + \beta policy_{gt} + \gamma COVID_{gt} + \psi provider_j + \tau week_t + \gamma market_s + \varepsilon_{jgt}$

Both our first stage and reduced form results leverage geographic variation in the implementation of social distancing as telehealth policies. While changes to reimbursement happen at the nationwide level, wide variation exists in both the timing and the intensity of market-level social distancing policies. In essence, we compare changes in patient demand and use of telehealth between regions such as New York City and San Francisco, which implemented social distancing policies in early March, with Alabama and Florida, which implemented policies in April, and with states like North Dakota and South Dakota, which during the time of our data did not implement policies.

In all sets of models, for our instrumented δ coefficient to have a causal interpretation, the standard instrumental variables assumptions must be met. First, the implementation of social distancing policies must predict changes in in-person demand. Perhaps not surprisingly, we find that regulations on social activities are strong predictors of changes in demand for in-person medical care. As discussed below, we find that overall, implementation of social distancing policies leads to an approximately 4 percent reduction in foot traffic to physician offices, after controlling for both the nationwide and county-level trajectories of the COVID-19 pandemic. Depending on the specification, our first-stage *F-statistic* values range from 39 to 21, which are well above conventional thresholds (Stock and Yogo 2005).

A second assumption relies on the absence of contemporaneous shocks that influence both unobserved use of in-person services and the use of telemedicine. Given the rapidly changing environment surrounding the COVID-19 pandemic, violations of the exclusion restriction assumption are particularly concerning. One potential example is changes in reimbursement for telemedicine policies (Shachar, Engel, and Elwyn 2020; Kaiser Family Foundation 2020; Center for Connected Policy 2020). For example, in response to concerns about in-person care exposing patients and providers to COVID-19 infections, the Centers for Medicare & Medicaid Services (CMS) authorized providers to bill for medical services provided through telehealth (Verma 2020), and many private insurers quickly followed. In such a situation, our observed estimates could simply reflect the changing reimbursement environment for telehealth, rather than changes in patient demand. Our week fixed effects control for these types of nationwide shocks that influence the use of telemedicine.

A second, and more challenging, concern is the potential that the social distancing policies we use as an instrument are endogenously implemented in response to local-market variations in the intensity of the COIVD-19 pandemic. States and counties that have little exposure to COVID-19 are unlikely to implement social distancing policies. In such a case, the reductions in patient demand we observe may be related to unobserved responses to variations in COVID-19 exposure that also lead to the implementation of social distancing policies, and not social distancing policies directly. Likewise, local market exposure to the COVID-19 pandemic could lead to both patient and provider behavioral responses that reduce use of in-person care.

We address this limitation by also including as instruments local-market variations in exposure to the COVID-19 pandemic. To do so, we use two approaches. First, we include indicators for the first COVID-19 death and case in the county from USA Facts (USAFacts

2020). These controls account for variations in the initial exposure to the COVID-19 pandemic, which could precipitate the implementation of social distancing polices. Second, we follow the approach used in previous work and non-parametrically control for local-market variations in the intensity of the COVID-19 pandemic by including fixed effects for the county-level number of weeks since the first COVID-19 case and death (Cantor et al. 2020). We do not include the number of COVID-19 cases or deaths in a county, as these measures are likely impacted by the implementation of social distancing policies.

Additionally, we estimate the effects of changes in county-level foot traffic on provider-level telemedicine calls. Potential violations of the exclusion restriction assumption that lead to reductions in in-person care and adoption of telemedicine should impact all providers in the market, in this case, counties. Finding similar provider-level use of telemedicine when using changes in foot-traffic to all physician offices in a county instead of foot traffic to that specific physician's location suggests that factors other than changes in patient demand for that specific provider lead to changes in use of telemedicine.

A related threat to identification is the potential that social distancing policies are implemented in response to changes in demand or unobserved factors that lead to social distancing behaviors. We examine this potential concern using an event study approach for both our first stage and reduced form results. While we do observe decreases in-person demand and increased trends in telehealth use in the weeks prior to the implementation of social distancing policies, social distancing behavior starkly decreases and use of telehealth rapidly increases following the implementation of social distancing policies. The sharp break in both in-person demand and use of telehealth services following the implementation of social distancing policies suggests that demand responds to social distancing policies, rather than the reverse.

A final potential concern with our approach is the accuracy of the matching process between our two datasets. As a solution, we also estimate regressions that use market-level changes in in-person office visits. These regressions thus estimate the effect of market-level changes in patient demand on firm-level (physician) use of telehealth.

4. RESULTS

4.1. First Stage: Effect of Social Distancing Policies on Patient Demand

In Table 1, we present the first stage results that estimate the change in in-person foot traffic to physician offices following the implementation of state and county-level social distancing policies. Consistent with existing studies and anecdotal evidence, we observe rapid declines in foot traffic to physician offices using the cellular phone GPS data following the implementation of shelter in place laws and in counties exposed to COVID. In column 1, which does not control for county-level exposure to the COVID-19 pandemic, the implementation of SIP policies leads to a 4.8 percent reduction in weekly foot traffic to physician offices.[1] Adding the indicator for the week of the first case does not change the effect (column 2). Adding the indictor for the week of the first case slightly reduces the coefficient magnitude to a 4.1 percent reduction (columns 3 and 4). Adding the non-parametric controls for weeks since the first COVID-19 case decreases the estimated effect to 3.7 percent (column 5), 3.6 percent when adding fixed effects for the weeks since the first COVID-19 death (column 6), and 3.3 percent when including both sets of fixed effects (column 7).

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

4.2. Reduced Form: Effect of Social Distancing Policies on Use of Telehealth

The first-stage reductions in in-person office visits are partially offset by increases in the use of telemedicine calls. Our reduced form results in Table 2 show that following the introduction of social distancing policies, provider-specific telemedicine calls on the Doximity platform increased by 1.7 percent when not accounting for variation in exposure to the COVID-19 pandemic (column 1), and by 1.5 percent when including the indicators for the week of the first COVID-19 case and death in a county. As in the first stage results, we observe similar-sized changes for both the SIP coefficients and the week of the first death. The similarity between the two supports including local-market variations in exposure to the COVID-19 pandemic in the set of instruments, rather than just the SIP policy indicators. Adding the non-parametric controls for the weeks since the first COVID-19 case reduces the estimated effect to a 1.3 percent increase, adding the weeks since the first COVID-19 death in the county decreases the effect to 1.2 percent, and including fixed effects for both measures leads to a 1.1 percent increase in the weekly number of calls per NPI.

Panel B performs the same exercise, but uses the binary probability of any calls on the platform at the NPI-week level. In column 1, when not accounting for differential exposure to the COVID-19 pandemic, we estimate an extensive-margin 0.6 percentage point increase in the likelihood of using the platform. Adding the indicators for the week of the first COVID-19 case and death in a county does not change the result. The coefficient in column 4 estimates a 0.5 percentage point increase in use. However, adding the flexible non-parametric controls meaningfully changes the results. The results in column 4 imply a 0.4 percentage point increase in use.

In Panel C, we estimate the change in calls among users to estimate the intensive-margin changes in calls. Across all seven specifications, the intensive-margin reduced form coefficients are approximately five times larger than the overall effects in Panel A. When not controlling for exposure to the COVID-19 pandemic, we estimate a 7.6 percent increase in call volume following the introduction of SIP policies. This effect falls slightly, to 7.1 percent, when including the indicators for the week of the first COVID-19 death and case (column 4). However, following the week of the first COVID-19 case in a county, weekly calls increase by 5.6 percent among active users. In column 7, we find a 6.3 percent in call volume among active users when non-parametrically controlling for exposure to the COVID-19 pandemic.

4.3. IV Results: Effect of Demand Shocks on Technology Substitution

Consistent with both the first stage and reduced form results, our instrumented results in Table 3 estimate the effect of reductions in in-person foot traffic with overall, extensive-margin, and intensive-margin adoption of the Dialer tool. The call volume dependent variables in Panels A and C are log-transformed, which allows for an elasticity interpretation of results. For each measure, we use the change in foot traffic to each NPI's location in columns 1-3. In columns 4-6, we use the placebo test of changes in county-level foot traffic to all physician offices.

In Panel A, we find that among all matched NPIs, only instrumenting for changes in foot-traffic using the implementation of SIP policies leads to an elasticity estimate of -0.35. However, the Kleibergen-Paap F-statistic is 5.5, which implies that using only SIP policies is not a sufficiently strong instrument. When adding the indicators for the week of the first COVID-19 case and death, the F-statistic increases to 39.4, and the elasticity estimate decreases to -0.23. Adding the weeks since the county-level first COVID-19 case and death decreases the elasticity estimate to -0.15.

Columns 4-6 use the county-level, rather than the NPI-level, change in foot traffic and show considerably smaller effects. For example, the results in columns 5 and 6, which include the full set of COVID-19 controls as instruments, show a -0.03 and -0.01 elasticity, which are approximately an order of magnitude smaller than when using NPI-specific changes in foot traffic. Thus, consistent with the causal mechanism motivating our analysis, physician adoption of the telemedicine tool is much more responsive to change in demand for that physician's services, rather than market-level changes in demand.

Panel B presents results for the extensive-margin outcome of any use of the telemedicine tool. In columns 2 and 3, we estimate that a 10 percent reduction in in-person foot traffic leads to 0.8 and 0.6-percentage point increases in the weekly likelihood of any telemedicine calls. To place these estimates in context, the mean probability of weekly calls during the 30th week of 2020 is 4.5 percent. Thus, the percentage-point increases translate to 18 percent and 13 percent relative increases, respectively. As in Panel A, we find minimal extensive-margin adoption of the tool in response to changes in county-level foot traffic to physician offices.

Finally, Panel C restricts the sample to active users of the tool to estimate intensive-margin effects. These results may have broader generalizability, as the results in Panel A do not consider use of other telemedicine applications. In column 2, we estimate an approximately -1.0 elasticity when instrumenting for COVID-19 exposure using the first case and death indicators. In column 6, we estimate a -0.3 elasticity when using the non-parametric fixed effects since the first COVID-19 case and death as instruments. The estimated elasticities are much smaller when using the county-level change in visits in columns 4-6.

Overall, the instrumented results indicate inelastic substitution between demand for in-person care and adoption of telemedicine during the COVID-19 pandemic. Our nationwide elasticity estimates range between -0.15 and -0.23, and between -0.99 and -0.30 when only considering active users of the platform we study.

5. DISCUSSION

How firms adopt new technologies is an important but largely unstudied economic question. In this paper, we leverage the shock of the COVID-19 pandemic, and policy responses to the pandemic, to study how physicians adopt a particular telemedicine platform. We leverage a unique linking of foot traffic physician offices from across the United States with call-log data on use of a popular telemedicine tool. We find that physicians adopt telemedicine in response to reductions in demand for in-person care but do so in an inelastic manner. Among all physicians, our main results imply a substitution elasticity between changes in foot traffic and calls on the telemedicine tool of -0.2. Among physicians who are regular users of the tool, we find an elasticity that ranges from -1.0 to -0.3. We also find that reductions in foot-traffic lead to the probability of any calls using the application.

Our results are limited to physician use of a single technology, and so our estimated results are likely to be conservative. While our results are limited to a single industry—the market for U.S. physician services—our finding that firms strategically adopt new technologies in response to changes in consumer demand, in this case patients, furthers understanding of firm behavior. We do not examine the network effects of physician adoption of telemedicine (Goldfarb and Tucker 2019) or heterogeneity in adoption (Oster 1982; Saloner and Shepard 1995) that are important for fully understanding firm adoption. Fully understanding these effects are especially important given the shock of the COVID-19 pandemic. Our estimates are also from the initial phase of the COVID-19 pandemic, and we do not consider how physicians will continue to use telemedicine and or return to in-person care as the COVID-19 pandemic evolves.

Our results also shed light on how health care delivery has transformed during the COVID-19 pandemic. Existing studies have used medical claims data to measure reductions in patient use of health services (Cantor et al. 2020; Whaley et al. 2020; Ziedan, Simon, and Wing 2020). However, medical claims data are limited to understanding changes in patient volume to providers because they are often segmented among specific payers or insurance providers. The mobility data used in this study provides a more comprehensive understanding of the changes in in-person care during the COVID-19 pandemic. Our findings of inelastic adoption of telemedicine suggests that many patient needs for health services are likely going unmet. Likewise, even if telemedicine services are able to generate similar revenue as in-person care, our findings suggest substantial disruptions to provider patient (i.e., customer) volume and revenues.

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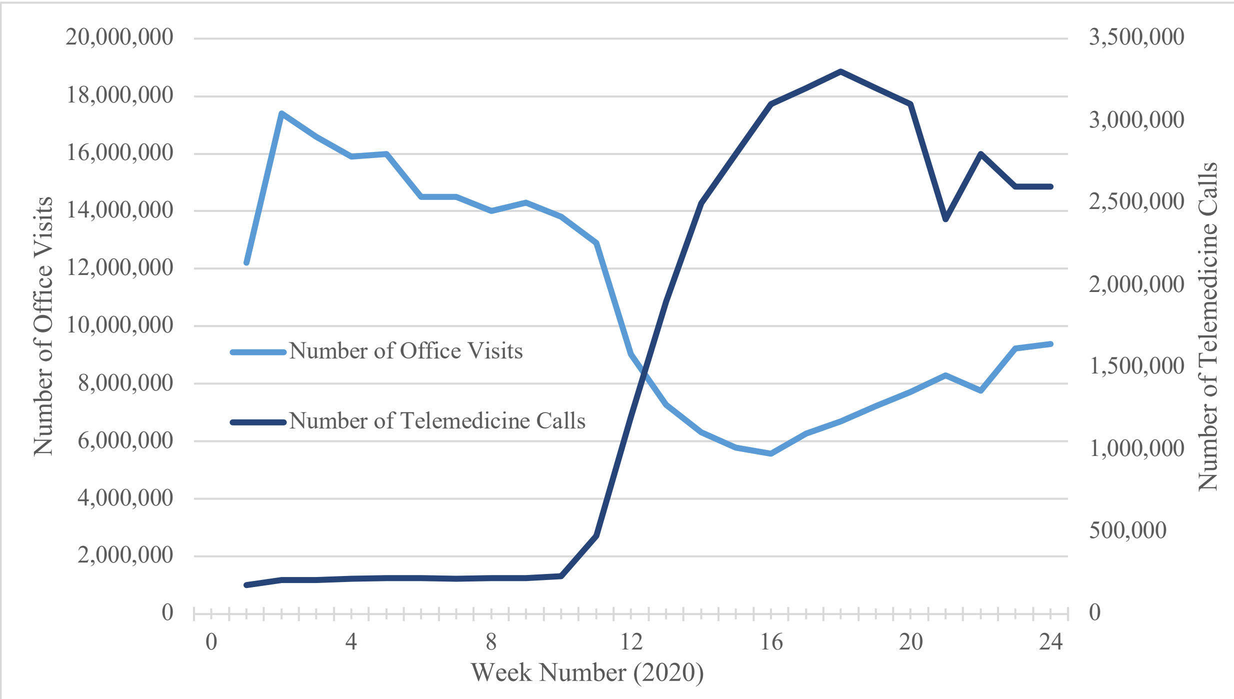
7. TABLES AND FIGURES

Figure 1: Unadjusted trends in in-person office visits and telemedicine calls



This figure shows unadjusted trends in the weekly number of foot-traffic visit to physician office locations (left axis) and calls on telemedicine calls on the Doximity platform (right axis).

Table 1: First Stage: Effect of social distancing policies and COVID-19 exposure on foot-traffic to offices of physicians

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in foot-traffic for all matched NPIs							
post SIP	-0.0492**	-0.0496**	-0.0416**	-0.0419**	-0.0379*	-0.0365*	-0.0334
	(0.0211)	(0.0211)	(0.0210)	(0.0209)	(0.0208)	(0.0206)	(0.0204)
first case		-0.00641		-0.00462			
		(0.0259)		(0.0249)			
first death			-0.0861***	-0.0860***			
			(0.0129)	(0.0126)			
Weeks since first case FE							
Weeks since first death FE					X		X
						X	X
Number of NPI							
Observations	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092
R-squared	0.884	0.884	0.884	0.884	0.884	0.885	0.885

This table presents the first stage estimates of the association between social distancing policies and foot-traffic to office of U.S. physicians. Columns 2 and 3 include indicators for the week of the first COVID-19 case and death in each county. Columns 5, 6, and 7 non-parametrically control for COVID-19 exposure by including fixed effects for the county-level weeks since the first COVID-19 case and death. Standard errors clustered at the county level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2: Reduced Form: Effect of social distancing policies and COVID-19 exposure on telemedicine use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Telemedicine use among all matched NPIs							
Dependent variable: ln(weekly calls + 1)							
post SIP	0.0170***	0.0163***	0.0155***	0.0148***	0.0129***	0.0119***	0.0108***
	(0.00410)	(0.00398)	(0.00397)	(0.00386)	(0.00373)	(0.00358)	(0.00349)
first case		-0.0113*		-0.0116*			
		(0.00601)		(0.00600)			
first death			0.0166***	0.0168***			
			(0.00221)	(0.00213)			
Weeks since first case FE					X		X
Weeks since first death FE						X	X
Number of NPI	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455
Observations	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092
R-squared	0.516	0.516	0.516	0.516	0.516	0.516	0.516
Panel B: Probability of telemedicine use							
Dependent variable: Pr(any weekly call)							
post SIP	0.00613***	0.00589***	0.00561***	0.00536***	0.00467***	0.00421***	0.00386***
	(0.00162)	(0.00158)	(0.00158)	(0.00154)	(0.00149)	(0.00142)	(0.00139)
first case		-0.00379		-0.00391			
		(0.00251)		(0.00251)			
first death			0.00574***	0.00581***			
			(0.000796)	(0.000775)			
Weeks since first case FE					X		X
Weeks since first death FE						X	X
Number of NPI	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455
Observations	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092
R-squared	0.523	0.523	0.523	0.523	0.523	0.523	0.524
Panel C: Telemedicine use among users							
Dependent variable: ln(weekly calls + 1)							
post SIP	0.0735***	0.0730***	0.0695***	0.0689***	0.0683***	0.0596***	0.0614***
	(0.0224)	(0.0225)	(0.0227)	(0.0227)	(0.0228)	(0.0216)	(0.0217)
first case		-0.00791		-0.00895			
		(0.0183)		(0.0185)			
first death			0.0542***	0.0544***			
			(0.0154)	(0.0152)			
Weeks since first case FE					X		X
Weeks since first death FE						X	X
Number of NPI	95,121	95,121	95,121	95,121	95,121	95,121	95,121
Observations	2,412,366	2,412,366	2,412,366	2,412,366	2,412,366	2,412,366	2,412,366
R-squared	0.477	0.477	0.477	0.477	0.477	0.478	0.478

This table presents the reduced form estimates of the association between social distancing policies and use of telemedicine, as measured through use of the Doximity Dialer tool. Use is measured as the log-transformed weekly number of calls (Panel A), the probability of any calls (Panel B), and the log-transformed weekly number of calls among users (Panel C). Columns 2 and 3 include indicators for the week of the first COVID-19 case and death in each county. Columns 5, 6, and 7 non-parametrically control for COVID-19 exposure by including fixed effects for the county-level weeks since the first COVID-19 case and death. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of changes in in-person foot traffic with telemedicine use

	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment Var: ln(NPI-level visits)			*Treatment Var: ln(County-level visits)*		
Panel A: Telemedicine use among all matched NPIs						
Dependent variable: ln(weekly calls + 1)						
ln(weekly foot traffic)	-0.345**	-0.227***	-0.152***	-0.121***	-0.0356**	-0.0112***
	(0.151)	(0.0363)	(0.0470)	(0.0327)	(0.0144)	(0.00170)
Instruments						
post SIP	X	X	X	X	X	X
first case and first death		X			X	
Weeks since first case and death FE			X			X
Number of NPI	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455
Observations	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092
Kleibergen-Paap F-stat	5.457	39.47	20.98	9.342	82.20	63.95
Panel B: Probability of telemedicine use						
Dependent variable: Pr(any weekly call)						
ln(weekly foot traffic)	-0.124**	-0.0796***	-0.0552***	-0.0437***	-0.0123**	-0.00460***
	(0.0538)	(0.0135)	(0.0180)	(0.0124)	(0.00600)	(0.000837)
Instruments						
post SIP	X	X	X	X	X	X
first case and first death		X			X	
Weeks since first case and death FE			X			X
Number of NPI	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455	1,084,455
Observations	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092	27,161,092
Kleibergen-Paap F-stat	5.457	39.47	20.98	9.342	82.20	63.95
Panel C: Telemedicine use among users						
Dependent variable: ln(weekly calls + 1)						
ln(weekly foot traffic)	-2.158	-0.985***	-0.297**	-0.948**	-0.0381	-0.0488**
	(2.774)	(0.280)	(0.141)	(0.476)	(0.0568)	(0.0197)
Instruments						
post SIP	X	X	X	X	X	X
first case and first death		X			X	
Weeks since first case and death FE			X			X
Number of NPI	2,412,366	2,412,366	2,412,366	2,412,366	2,412,366	2,412,366
Observations	2,412,366	2,412,366	2,412,366	2,412,366	2,412,366	2,412,366
Kleibergen-Paap F-stat	0.759	11.11	19.73	3.327	54.63	55.06

This table presents the instrumental variables results that estimate the effect of changes in foot traffic on use of telemedicine, as measured through use of the Doximity Dialer tool. Use is measured as the log-transformed weekly number of calls (Panel A), the probability of any calls (Panel B), and the log-transformed weekly number of calls among users (Panel C). Columns 1-3 measure provider-specific changes in foot traffic while columns 4-6 measure county-level changes in foot traffic to physician office locations. Columns 2 and 5 includes indicators for the week of the first COVID-19 case and death in each county. Columns 3 and 6 non-parametrically control for COVID-19 exposure by including fixed effects for the county-level weeks since the first COVID-19 case and death. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.