On the Demand for Telemedicine:

Evidence from the Covid-19 Pandemic

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Inter-American Development Bank

April 2021
Abstract

Telemedicine can expand access to health care at relatively low cost. Historically, however, demand for telemedicine has remained low. Using administrative records and a difference-in-differences methodology, we estimate the change in demand for telemedicine experienced after the onset of the COVID-19 epidemic and the imposition of mobility restrictions. We find a 230 percent increase in the number of telemedicine calls. The effects were mostly driven by older individuals with pre-existing conditions who used the service for internal medicine consultations. The demand for telemedicine remained relatively high even after mobility restrictions were relaxed, which is consistent with telemedicine being an experience good. These results are a proof of concept for policymakers willing to expand access to healthcare using advances in technology. JEL Codes: I11, I15, P36

Keywords: Coronavirus, COVID-19, Health care demand, Telemedicine, Argentina.

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1 Introduction

Telemedicine can be a powerful tool to expand the delivery of health care services at a relatively low cost (Bashshur, 1995; Ekeland et al., 2010). Even though technological innovations have eased the expansion of the supply of telemedicine services in recent years (Pandian, 2016), its demand has remained stubbornly low (Wootton, 2008; Zanaboni and Wootton, 2012). The COVID-19 pandemic seems to have changed that. The pandemic led many governments to impose lockdown and social distancing policies which induced patients around the world to experience telemedicine for the first time.

In this paper, we exploit the introduction, and later relaxation, of social distancing policies to study how the demand for telemedicine changed in Argentina. We rely on administrative records from one of the largest providers of telemedicine in the country to build a panel data set that includes daily records of all calls received during 2019 and 2020. We use an event study and a difference-in-differences methodology to estimate the change in demand for telemedicine that happened after mobility was restricted at the onset of the COVID-19 epidemic.

We find that the use of telemedicine, as captured by the total number of calls and calls from first-time callers, increased 230 and 198 percent, respectively. There was an increase in resolved consultations (of 235 percent) and in calls referred to another specialist (190 percent). Telemedicine calls resulting in prescriptions increased 332 percent. These effects were driven mostly by older individuals with pre-existing conditions who used telemedicine for internal medicine consultations. As spatial mobility began to increase, reaching 80 percent of the pre-pandemic levels, we find that the use of telemedicine declined slightly and not quickly enough to converge to the pre-pandemic period. A 1 percent increase in mobility resulted in 0.8-2.5 percentage points decrease in the use of telemedicine. Although more time is needed to fully assess whether this demand will remain as high when mobility is fully restored, we take this results as tentative evidence that the upward shift in demand is likely persistent.
There are several reasons why people may resist the use of new technologies such as telemedicine (Broens et al., 2007). First, there could be a general mistrust or lack of information from patients and health professionals about the effectiveness of telemedicine (Mair et al., 2007). Second, there are real—even if small—convenience factors, such as having to download and set up the technology, that could discourage its use or trigger procrastination (Baicker et al., 2012; Bertrand et al., 2004; Kremer et al., 2019; Madrian, 2014; Rice, 2013). Third, there are a number of behavioral biases that may limit the use of telemedicine. Individuals also may not download the applications required to use telemedicine services because of present bias, which makes them undervalue the future gains of having the service ready to be used when they are sick (Kang and Ikeda, 2016; Kremer et al., 2019; Linnemayr and Stecher, 2015; Madrian, 2014; Williams et al., 2018). This can be particularly problematic if they also have optimism bias, which leads patients to underestimate the probability of negative events, or if they worry that using telemedicine could jeopardize having access to in-person visits later on (i.e., loss aversion) (Kahneman et al., 1991). These biases build on a reticence by consumers to move from a known status quo to newer alternatives (Hartman et al., 1991; Kahneman et al., 1991; Rice, 2013; Suri et al., 2013; Tsai et al., 2019; Zhang et al., 2017).

Our paper exploits an external shock that triggered patients’ learning about telemedicine. As is the case with many health care services, telemedicine can be characterized as an “experience good”: one that can only be accurately evaluated—and compared to its substitute, in-person visits—only after the product has been purchased and experienced (Andersen and Philipsen, 1998).1 By showing that demand dramatically increased after the onset of the COVID-19 epidemic and presenting preliminary evidence of persistence of those effects, our results contribute to the large literature that analyzes patient learning about healthcare markets. Similar learning processes have been shown, for instance, to reduce the costs of un-
certainty in pharmaceutical markets (Crawford and Shum, 2005), to increase the take up of new vaccines (Maurer and Harris, 2016), and to affect the choice of health insurance plans (Chernew et al., 2008).²

This paper also contributes to the strand of the literature that studies how demand for new health care services is affected by exogenous changes in factors such as service price (Berman and Fenaughty, 2005), beliefs and social norms (Cranen et al., 2011), education and household wealth (Chunara et al., 2020). We conjecture that the epidemic, by restricting access to traditional in-person visits, induced consumers to overcome behavioral constraints and use telemedicine for the first time. This experience with the service seems to have led to a new equilibrium of higher demand, which adds evidence to the literature on experience goods and the adoption of new technologies (Sunstein, 2019).

Finally, our results contribute to the new and expanding literature on the effects of the COVID-19 crisis on the demand for services including online education (Ikeda and Yamaguchi, 2020), online retailers (Farrell et al., 2020), child care (Ali et al., 2020), and public transportation (Tirachini and Cats, 2020).

From a public health point of view, the importance of telemedicine as “forward triage” to sort patients before they arrive at the hospital has been of paramount importance during a pandemic. Telemedicine allows patients to be efficiently screened and directed to the most suitable health care provider, which effectively increases the capacity of the health care system (Hollander and Carr, 2020), and allows to isolate those who may be infected by the virus. Our paper shows that telemedicine, when properly deployed and scaled up, can be relied upon as an important tool for public health management.

This paper is organized as follows. Section 2 reviews the literature on cost and benefits of telemedicine. Section 3 describes the setting in which the increase in the demand for telemedicine services took place. Section 4 shows how mobility declined in Argentina during

²Learning about new health care products matters not only in the case of patients but also in the case of physicians (Ferreyra and Kosenok, 2011). This learning process can potentially diffuse through the economy (Coscelli and Shum, 2004).
the COVID-19 crisis. Section 5 specifies the empirical strategy and the data used in the analysis. Section 6 presents the results, and Section 7 concludes.

2 Costs and Benefits of Telemedicine

The terms telemedicine or telehealth are currently used to describe the provision of health care services remotely, by means of a variety of telecommunication tools including telephones, smartphones, and mobile devices, with or without a video connection (Dorsey and Topol, 2016). In recent years, the use of telemedicine has gained momentum, primarily because of the perceived potential to better distribute and control the use of medical services, which would lead to improvements in timeliness of delivery and, hence, in the overall quality of health care. Indeed, telemedicine has been proven to increase the accessibility of health services, as well as to reduce travel time and related opportunity costs in the process of obtaining care (Bashshur, 1995). From war veterans to patients in rural areas, telehealth provides an alternative to traditional healthcare that lowers the time and cost of receiving service (Jacobs et al., 2019; Sabesan et al., 2012). In addition, there is evidence that telemedicine is successful in reducing the need for ambulance transport, which could provide relief to the overcrowded healthcare system (Langabeer et al., 2016). Telemedicine can also increase the diversity of care to which an individual has access. As an example, for indigenous groups, telemedicine provides an option that reduces the burden of travel and dislocation from community and family (Caffery et al., 2018).

The effectiveness of telemedicine depends greatly on where it is being deployed. A scoping review of the use of telemedicine concluded that, when comparing the effectiveness of electronic and face-to-face consultations, the evidence shows ambiguous results (Caffery et al., 2016; Roine et al., 2001). Replacing traditional face-to-face patient care can potentially result in a breakdown of the traditional relationship between health professional and patient,

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3 As the use of new communication technologies expanded in the late 1990s, telemedicine was implemented for patients with acute traumas and stroke (Levine Steven R. and Gorman Mark, 1999).
caused by the potential depersonalization of the service (Hjelm, 2005). Evidence shows, however, that this idea of service depersonalization might be a misconception. In practice, reported quality and satisfaction levels of patients who use telemedicine are overwhelmingly positive (Jacobs et al., 2019; Kruse et al., 2017; Polinski et al., 2016). For many patients, electronic consultations were preferred for convenience and travel time (Donelan et al., 2019). In spite of this, there is still a reluctance on the part of patients to increase their use of telemedicine (Wootton, 2008).

It is also important to recognize other practical costs that telemedicine presents. With the adoption of telemedicine as a cheaper and more convenient alternative, there is the potential for excess health care utilization (Ashwood et al., 2017; Bavafa et al., 2018). That is, there is still the open question if the overall increase in demand that could result from the surge of telemedicine would serve a previously unmet need for healthcare or if, on the contrary, it would produce an overuse of health care services. Another concern is the possibility of over-prescription (Sprecher and Finkelstein, 2019). Similarly, legal and reimbursement issues could arise from limited or fragmented health care coverage through telemedicine services (Dorsey and Topol, 2016). The solution to these problems relies on the existence of a legal framework that appropriately regulates the use of telemedicine within the broader healthcare system.

In spite of these limitations, the health care community has encouraged the shift from an in-person care model to a model of virtual care (Duffy and Lee, 2018). The COVID-19 crisis highlighted the need for an easily deployable, mobility-reducing, and low-cost alternative to deliver care, especially to more at-risk populations. The pandemic rapidly increased the perceived benefits of telemedicine and lowered its costs. Moreover, high mobility restrictions imposed by governments pushed individuals to experience telemedicine first-hand, which reduced the barriers associated with experience goods and made more patients find telemedicine a suitable substitute for in-person care (Accenture, 2020).
3 Telemedicine in Argentina

Before the onset of the COVID-19 pandemic, the government of Argentina had already recognized the use of telemedicine as one of the main pillars of its strategy to ensure universal health coverage. In 2019, the government launched its digital health strategy, which included among its goals the expansion of telemedicine as a tool to provide health services to geographically remote populations, improving accessibility, reducing the need for medical-related transportation, and compensating for regional differences in access to health care (Gobierno de Argentina, 2019). Once the COVID-19 pandemic lockdown begun, the government encouraged private health insurance providers to foster the use of telemedicine (Superintendencia de Servicios de Salud, 2020). At the onset of the pandemic, two providers of telemedicine services had most of the market share in the country. One such provider was “Llamando al Doctor” (or “Call your Doctor”) which offered services to health care providers, insurance companies, and individual patients all across the country. At the end of 2019, the firm employed 108 doctors covering 11 medical specialties, including general medicine, pediatrics, and gynecology and obstetrics.

Patients access the service primarily through a mobile phone application, where they are asked a series of screening questions: the medical specialty they require, the reason for their consultation, and any previous conditions they may have. Following the screening questions, they proceed to the online consultation with a physician through a video call. Each video call can result in one of three different outcomes. The first, and most common one, is when the doctor is able to resolve the patient’s issue during the online consultation (this is the case for 67 percent of the calls in 2019). In some of these calls, patients are prescribed a medicine (9 percent of the overall calls). A second outcome is a recommendation of a follow-up call (8 percent of the calls). A third outcome of the video call could be that the doctor refers the patient to an in-person visit (11 percent of the calls).

4The other provider of telemedicine in Argentina is called “Doc24”.
5In about 14 percent of calls, the call is disconnected or the video call does not take place for technical issues.
Each call produces a log that registers the patient’s gender, age, and specialty requested as well as a description of the reason for and the diagnosis resulted from the call. Table 1 provides some descriptive statistics for 2019 based on this (anonymized) administrative data. Patients that use telemedicine are relatively young (30 years old on average) and more likely to be women (57%). The majority of consultations relate to general medicine and pediatrics.

Table 1: Telemedicine Service 2019
Descriptive Statistics

|                             | Average | Std. Dev. | Obs. |
|-----------------------------|---------|-----------|------|
| Resolved                    | 66.6%   | 47.2%     | 6890 |
| Prescription                | 11.5%   | 31.9%     | 1191 |
| Follow-up                   | 8.3%    | 27.6%     | 857  |
| Referral                    | 10.8%   | 31.1%     | 1121 |
| General Medicine            | 45.8%   | 49.8%     | 4740 |
| Ob/Gyn                      | 18.5%   | 38.8%     | 1909 |
| Pediatrics                  | 35.7%   | 47.9%     | 3691 |
| Age                         | 30.5    | 15.1      | 10340|
| Male                        | 43.1%   | 49.5%     | 4455 |
| Previously Diagnosed        | 25.0%   | 43.3%     | 2585 |

Note: Author’s calculations based on administrative records of “Llamando al Doctor”. The first panel shows the outcomes of telemedicine calls, the second panel the reason/type of calls, and the third panel the basic characteristics of the caller.

4 Mobility during the COVID-19 Crisis

As a consequence of the COVID-19 pandemic governments around the world enacted different policies in an effort to contain the propagation of the virus and to minimize its social impact (Hale et al., 2020b). These measures included mobility restrictions, economic relief programs, and investment in the health care system.

The pandemic started to unfold in Argentina at the end of February 2020. Media coverage and online searches of COVID-19 related terms started to increase on the week of
February 20 (the eighth week of the year). The first case of COVID-19 was recorded on March 3.  

Argentina’s government’s issued the first social distancing measures on March 15 when schools were mandated to close. Three days later the government issued a formal, and strictly enforced, stay-at-home order for most of the country’s population. By March 22, restrictions on public transportation were put in place. The timing and severity of the lockdown policies can be summarized using a Stringency Index\(^7\) which rapidly reached a maximum of 100 by March 23, when the country reported the first four confirmed deaths by COVID-19 (Hale et al., 2020\(^a\)). The government’s fast and stringent response placed Argentina amongst the countries with the strictest lockdown measures in Latin America.\(^8\) De jure, these measures remained in place until November 2 when lockdown measures were formally relaxed.\(^9\)

These measures severely affected people’s spatial mobility; especially at the beginning of the pandemic. We use publicly available data to build three indicators of observed mobility. The first two indicators come from the Apple Mobility Trends Report, which keeps track of driving and walking directions (Apple, 2020). The information shows the volume of directions requested relative to the baseline volume in January 2020. A third indicator comes from Moovit, a company that provides a daily report of the use of its popular mobile application for public transit relative to the use in the week prior to January 15, 2020 (Moovit, 2020).

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\(^6\)Our data shows that a COVID-19 related consultation was first recorded in a telemedicine call on March 1.

\(^7\)The Stringency Index, published by the University of Oxford, is a composite index that considers nine indicators including school closures, workplace closures, and travel bans that governments could take in face of the COVID-19 pandemic. This index ranges from 0 to 100, with 0 being no measures taken and 100 being all nine measures taken in their strictest version (Hale et al., 2020\(^a\)).

\(^8\)For context, other countries in the region like Colombia reached a Stringency Index of 90.74 on March 27 with 243 confirmed deaths; Brazil reached an Index of 81 by May 5 with 7,321 confirmed deaths, and Chile reached an Index of 78.24 by May 15 with 358 confirmed deaths (Hale et al., 2020\(^a\)).

\(^9\)There was some regional variability in the timing of the relaxation of social distancing restrictions.
Figure 1: Mobility Indicators in Argentina for 2020

Note: The figure plots indicators of spatial mobility. Walking and driving data was obtained through the Apple’s Mobility report using baseline volume from January 13 2020. The public transit indicator comes from Moovit using baseline volume in the week of January 15 2020. An indicator with value 100 means that in that day the mobility was the same as the reference dates.

Figure 1 shows that the three indicators of mobility experienced a sharp decline around March 12, 2020. Even though many of the measures limiting mobility remained in place for months to come, walking and driving started to slowly and steadily increase over time. The use of public transportation remained depressed throughout the winter months (when lockdown measures were still in place) and started to increase after September. By the end of the year, mobility indicators were closer to their pre-pandemic levels.\footnote{These indicators could be underestimating the true increase in mobility because changes of other behav-}
5 Empirical Strategy

We use administrative records from “Llamando al Doctor” to construct a panel data set with the records of all calls received during the period of January 1 through December 31 for the years 2019 and 2020. These data allow us to analyze changes in the volume of daily calls received and in the daily number of first-time callers. We also observe the outcome of these telemedicine consultations: whether they were resolved, required a follow-up, or referred to another specialist. In addition, we observe if calls resulted in the issuance of prescriptions.

We estimate the effect of the mobility restrictions associated with the COVID-19 epidemic on the demand for telemedicine using an event study and a difference-in-differences methodology.\(^{11}\) We define the onset of the pandemic (i.e., our ”treatment” date) as occurring during the eleventh week of the year when mobility restrictions became into effect. Because mobility declined abruptly on March 12 we define a week to be a seven-day period starting on each Thursday so that week 11 is the period from March 12 to March 18. A simple before and after comparison would not account for possible seasonal changes in demand for telemedicine. Thus, we compare outcome variables before mobility was restricted relative to their levels on the same date in 2019.

We begin by estimating an event study model based on the following equation:

\[
Y_{dwt} = \alpha + \sum_{\tau=2}^{49} \left\{ \beta_{\tau} \times 1(Week = \tau)_{dwt} \times Year2020_{dwt} \right\} + Year2020_{dwt} + \gamma_w + \delta_{dow} + \epsilon_{dwt} \tag{1}
\]

where \(Y_{dwt}\) is the outcome variable measured at day \(d \in (1, ..., 365)\) of week \(w \in (1, ..., 49)\) of year \(t \in (2019, 2020)\).\(^{12}\) \(1(Week_{\tau})_{dwt}\) is an indicator variable equal to one if day \(d\) of year \(t\) belongs to week \(\tau\) of that year, and \(Year2020_{dwt}\) is an indicator for dates during the year that occurred during the pandemic. For example, people may have switched to shops that were closer to their house, which these indicators would not capture (Pan et al., 2020).

\(^{11}\)Similar approaches were used, for instance, by Leslie and Wilson (2020) to study the effect of the mobility restrictions imposed during the COVID-19 pandemic on domestic violence.

\(^{12}\)The model can only be estimated for 49 weeks because we lack data for weeks 6, 7, and 8 of 2019 and week 17 of 2020. During those dates there were telemedicine calls but a server failure prevented “Llamando al Doctor” from storing the data.
2020. The coefficients $\beta_\tau$ estimate weekly changes in the outcomes for the period of January 1 to December 31 relative to the outcome variable in 2019. $\gamma_w$ are week fixed effects which control for seasonal trends and $\delta_{dow}$ are day-of-week fixed effects which control for differences in the volume of calls received that vary within the week. The base week category is week 5 when the first news about COVID-19 started to be discussed in the local media.

We also estimate average treatment effects according to the following difference-in-differences model:

$$Y_{dwt} = \alpha + \theta \text{Post}_{dwt} \times \text{Year}_{2020_{dwt}} + \text{Year}_{2020_{dwt}} + \gamma_w + \delta_{dow} + \epsilon_{dwt}$$

where $\text{Post}_{dwt}$ is an indicator variable which equals one for dates during or after week 11 of the year. In this model, $\theta$ captures the average change in the outcome variable after mobility was restricted, relative to the same period in 2019. One key assumption of our difference-in-differences specification is that in the weeks prior to the onset of COVID-19 pandemic the outcome variable in both years followed the same trend.\(^{13}\)

6 Results

We start by plotting the coefficients $\beta_\tau$ and the 95 percent confidence intervals from the event-study specification described in equation (1).\(^{14}\) Figure 2 shows the results for two outcomes: the log of the number of daily calls (panel A) and log of first-time callers (panel B). In both figures we overlay the times series of spatial mobility measured as the simple average of the three time series shown in Figure (1).

\(^{13}\)Notice that the estimated parameters measure the effect of the Covid-19 crisis on the demand for telemedicine from one major provider. They do not capture the effects on other suppliers.

\(^{14}\)The full raw time series daily data of our main outcome variables are presented in Appendix A.1 and Appendix A.2.
Note: The green line shows the simple average of walking, driving and public transit mobility indicators shown in Figure 1. Blue dots correspond to the point estimates obtained using equation (1) and blue bars show the associated 95% confidence intervals. The vertical dashed line marks week 11, when mobility restrictions were first imposed. Weeks 6-8 are missing because telemedicine calls were not recorded in 2019. Week 17 is missing because telemedicine calls were not recorded in 2020.

The event study allows to check for parallel trends during the pre-treatment period. The coefficients for the number of daily calls and first-time callers follow a flat pre-trend before week 5 and start to increase somewhat two weeks before the mobility restrictions came into effect (when the risks of getting infected was already being discussed in the media). We take this as evidence that the parallel trend assumption is valid for our main outcomes of interest.\textsuperscript{15}

\textsuperscript{15}Table Appendix A.1 presents the p-values of test of the following null hypothesis: $H_{0}^{1,4}: \beta_{j} = 0 \forall j \leq 4$ and the null that $H_{0}^{9,10}: \beta_{j} = 0$ for $j = 9, 10$ for each of the six outcomes analyzed in the paper. We fail to reject the $H_{0}^{1,4}$ for all six outcomes. However, we do reject $H_{0}^{9,10}$ at standard level of statistical significance in the case of three outcomes (number of telemedicine calls, number of first time calls, and calls that resolved
By week 11, when mandated social distancing entered into effect and mobility dropped, the estimates for the daily number of calls and first-time callers rose substantially. After that week, there was an upward trend in telemedicine use that reached a maximum by week 16. As mobility slowly started to converge to the pre-lockdown values we observe a mild decrease in the point estimates, which remained persistently higher than before the pandemic. These results point to an increasing demand for telemedicine that persisted even after mobility began to slowly go back to the pre-pandemic levels.

Table 2: Difference-in-Differences Estimates

| Main Effects | Call Resolution |
|--------------|-----------------|
| Calls        | First-Time Callers | Resolved | Prescription | Follow-Up | Referral |
| Post x Year 2020 | 2.297*** (0.078) | 1.976*** (0.080) | 2.350*** (0.078) | 3.324*** (0.102) | 3.052*** (0.114) | 1.899*** (0.101) |
| Week F.E. Yes | Yes             | Yes      | Yes          | Yes       | Yes       |
| Day of Week F.E. Yes | Yes             | Yes      | Yes          | Yes       | Yes       |
| Observations 690 | 690             | 690      | 690          | 690       | 690       |
| Adjusted R² 0.968 | 0.947           | 0.964    | 0.959       | 0.940     | 0.904     |
| Average Before | Week 11 2020 | 30.58    | 18.42       | 19.28      | 5.77      | 2.52      | 3.56 |

Note: Each column presents the results of the difference-in-differences specification for a different dependent variable, estimating $\theta$ in equation (2) using Ordinary Least Squares. The dependent variables use in these models are from left to right: log(number of calls), log(number of first time callers), log(number of resolved calls), log(number of calls resulting in prescription), log(number of follow-up calls + 1), and log(number of referrals + 1). All models include week fixed effects (F.E.) and day of the week fixed effects (F.E.). The last line shows the average of the dependent variable in levels (i.e., not in logs) before the implementation of the mobility restrictions. * statistically significant at 10%; ** at 5%; *** at 1%

Table 2 shows the results obtained with the difference-in-differences model described in equation (2). The increase in calls and first-time callers in the months after the pandemic was 230 and 198 percent, respectively. The effect of mobility restrictions vary across call the patient’s concern). This suggests that some behaviors had started to change a weeks before the formal lockdown started.

As a robustness, we estimated the event-study specification including health insurance provider fixed effects (to control for an expansion in the number of providers that offered the telemedicine service as an option). Figure Appendix A.3 shows the results which are essentially unchanged.
resolution outcomes. The largest effect was observed on calls resulting in prescriptions, which experienced an increase of 332 percent. There was also a large increase in calls that required some type of follow-up (305 percent). In addition, the increase in resolved consultations (of 235 percent) was larger than the increase in calls referred to another physician, which saw an increase of 190 percent.

\textit{Heterogeneity.}– We next explore which types of patients were more likely to shift towards telemedicine. To that end, we estimated the coefficients in equation (2) for different subgroups. Estimates of $\theta$ and 95\% confidence intervals are presented in Figure 3. The specialty with the greatest increase in demand was general or family medicine, which experienced an increase of 290 percent in the number of daily calls. Older patients increased the demand for telemedicine more than younger patients: the group 55-65 years old increased the use of telemedicine by 367 percent in the number of daily calls, while the group older than 65 experienced an increase of 406 percent after the social distancing measures were implemented. We also find that calls from patients who reported being previously diagnosed with a disease or illness increased by 296 percent. We find no differences between men and women in the increase of demand for telemedicine.
Figure 3: Treatment Effects: Heterogeneity

(a) Effects on log(Calls)

Note: Panel (a) shows Ordinary Least Squares estimates of $\theta$ in equation (2) for the different subgroups specified on the x-axis. “Baseline” reports the main results of Table 2 (for reference we place a horizontal dotted bar at that level). “General Medicine” shows the effect on log(calls) related to general medicine. “Ob/Gyn” shows the estimated effect on log(calls) regarding obstetric or gynecological care, and “Pediatrics” the effect on pediatric consultations. “<18”, “18-24”, “25-39”, “40-54”, “55-64” shows the estimated effect on people in those age categories. “Male” and “Female” estimate the effect for patients of different sex. Finally “Previously Diagnosed” shows the estimated increase in calls by patients with a previous diagnosis. Panel (b) depicts the same estimates when the outcome is log(number of first-time callers). Blue bars report the 95% confidence intervals.

Long-run effects.– If telemedicine is an experience good, once people start using the service they might continue to use it in the future even when the possibility of visiting the doctor in their office is again a possibility. Figure 2 shows that mobility steadily increased in the months after the initial lockdown period and, contemporaneously, weekly changes in the number of calls declined slightly throughout the same period. We exploit this variation to approximate an elasticity of demand of telemedicine to mobility by looking at the correlation
between mobility and weekly changes in the outcome variables using the following regression:

\[
\hat{\beta}_\tau = \alpha_0 + \alpha_1 \Delta Mob_\tau + \nu_\tau
\]  

(3)

where the dependent variable \(\hat{\beta}_\tau\) is the weekly change in outcomes estimated for week \(\tau\) using equation (1), and \(\Delta Mob_\tau\) is the simple average of the three indicators of mobility during week \(\tau\) of 2020 relative to January 2020 (as shown in Figure 1). We estimate this model for the full sample and for the weeks after week 11, when mobility was restricted and later relaxed.

Table 3: Demand for Telemedicine and Spatial Mobility

|                | All 2020 | 2020 Post Week 11 |
|----------------|----------|-------------------|
| \(\beta_{Calls}\) | \(\beta_{Callers}\) | \(\beta_{Calls}\) | \(\beta_{Callers}\) |
| \(\Delta Mob\)      | \(-0.026^{***}\)  | \(-0.025^{***}\)  | \(-0.008^{***}\)  | \(-0.016^{***}\)  |
|                   | (0.003)   | (0.002)           | (0.003)           | (0.003)           |
| Obs.               | 48        | 48                | 42                | 42                |
| Adjusted \(R^2\)  | 0.621     | 0.735             | 0.161             | 0.457             |

Note: Each column presents the Ordinary Least Squares estimate of \(\alpha_1\) in equation 3. The first two columns present results for the full sample. The third and fourth columns presents the results estimated using only the weeks after week 11. * statistically significant at 10%; ** at 5%; *** at 1%

Table 3 shows the results. A 1 percent increase in the average mobility results in a 0.8-2.6 percent point reduction in the demand for telemedicine (measured by the number of calls). The estimates suggest that, despite travelling more, patients do not completely shift back to in-person consultations and were still opting for telemedicine as an alternative even at the end of the year when mobility was closer to pre-pandemic levels. As mobility increased, the number of first-time callers also decreased but only slightly. This suggests that the expansion of telemedicine both by adding new patients and by the extensive margin may continue even after in-person consultations are possible again.17

17Appendix Table Appendix A.2 shows the results of estimating equation (3) on other outcomes. The
Our results are consistent with survey evidence of more than 2,700 patients (conducted in China, France, Germany, Japan, the United Kingdom and the United States) which showed that about 60 percent of respondents said that they want to keep using the technology based on their experience with it during the pandemic (Accenture (2020)). We take our results as tentative evidence suggesting that the demand for telemedicine did not decline sharply as mobility increased. More time and data are needed to better assess how permanent the increase in demand is.

Discussion. The magnitude of our results are in line with the previous literature. Barnett et al. (2018) find that the use of telemedicine increased 261 percent as a result of expanded coverage on telemedicine services by medicaid and private insurers in the United States. Harvey et al. (2019) find a 30 percent increase in the use of telemedicine as a result of expanded insurance coverage for telemedicine through state-level legislative change. Park et al. (2018) report a 228 percent increase in telehealth video calls when video-consultation was integrated as a service. Der-Martirosian et al. (2020) find an increase in the use of telemedicine of 50-205 percent in the context of a natural emergency (the 2017 Atlantic hurricane season).

The increase in the use of telemedicine in our specific setting could in principle be explained by two channels. First, an increase in the overall number of consultations (both in-person and remotely), to some extent because of the pandemic itself. Second, a substitution effect by which patients switched from in-person to telemedicine consultations. Unfortunately, we do not observe in-person consultations for most patients in our data that would allow us to disentangle these two channels. We offer, instead, tentative evidence consistent with telemedicine partly substituting in-person consultations.

First, the share of first-time callers in the total number of telemedicine calls dropped from 60 percent at the onset of the pandemic to about 30 percent by the end of 2020. This is change in resolved calls also decrease by 1 percent as mobility increases 1 percent. The number of follow-up calls, referred calls and calls that concludes with a prescription do not experience significant changes as mobility returns to pre-pandemic levels.
consistent with the conjecture that telemedicine is an experience good. Patients might have been hesitant to use telemedicine for the first time but, as they started using the service, they continued to do so throughout the year. In fact, about 65 percent of patients in our data are recurrent users of telemedicine, meaning that they called multiple times after their initial call.

Second, we obtained data from a health insurance provider associated that offers the service of telemedicine to its affiliates. We find that initially, as mobility restrictions were imposed, patients seem to have substituted in-person with telemedicine consultations. As mobility increased, however, the number of in-person consultations increased and telemedicine decreased somewhat but, at least so far, it seems to have stabilized at a higher level than before mobility was restricted. This is consistent with the estimation results of equation (3).

7 Conclusion

Using administrative records from one of the largest providers of telemedicine in Argentina and a difference-in-differences methodology, we find that the demand for telemedicine, as captured by the number of calls and first-time callers, increased 230 and 198 percent, respectively, after the onset of the COVID-19 pandemic. While both increased, first-time callers as a share of the total dropped from 60 percent at the onset of the pandemic to 30 percent later on, which is consistent with telemedicine being an experience good. The largest effect was observed on calls resulting in prescriptions, which experienced an increase of 332 percent. There was also an increase in resolved consultations (of 235 percent) and in calls referred to another specialist (190 percent). The effects were driven mostly by older individuals with pre-existing conditions who used telemedicine for internal medicine consultations.

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18 These data is not necessarily representative of the all users of telemedicine. The patients of this health insurance company tend to be older, more likely to be male, and more likely to have a pre-existing condition than the rest of the patients that interact with the telemedicine provider. See Appendix Table Appendix A.3.

19 See Appendix Figure Appendix A.4.
Our paper is the first one to document the existence of an untapped demand for telemedicine services in a middle-income developing country. We also show that the increase in the use of telemedicine slightly decreased after mobility restrictions eased but not enough to undo the increase in demand. However, our study has two important limitations. First, more time and data is needed to assess whether the use of telemedicine after the pandemic is resolved will remain high. Second, because we lack information on in-person consultations for each patient we are not able to fully assess to what extent the increase in the demand for telemedicine substituted in-person consultations.

Prior to the COVID-19 pandemic, many governments as well as the World Health Organization viewed telemedicine as a tool to increase access to healthcare, reduce healthcare costs, and expand service, particularly to geographically remote and underserved populations (WHO, 2016). The COVID-19 pandemic made even more clear the need to adopt innovative solutions that can provide relief to the saturated health care system, helping to meet increasing demand while minimizing the risk of transmission. This paper is a proof of concept that there was a hidden demand for telemedicine and that policymakers have space to foster and accelerate the adoption of technological solutions for health care delivery (Tannerverdi and Iacono, 1999). Behavioral tools could help to lower barriers and nudge people into using this service and ripping its benefits. Providing patients the ability to experience the service could go a long way toward ensuring sustained use.
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Appendix Tables and Figures

Figure Appendix A.1: Trends in Daily Number Calls 2019-2020

Figure Appendix A.2: Trends in Daily First-Time Callers 2019-2020

Note These figures show the time series for the log of daily number of calls and daily number of first time callers received by “Llamando al Doctor” for the period 2019-2020.
Figure Appendix A.3: Treatment Effects: Event-study Analysis Client Fixed Effects

(a) Effects on log(number of calls)

(b) Effects on log(first time callers)

Note: To further test our results we restricted our data to take only 7 clients of Llamando al Doctor that represent 90% of the observations in the data set. Moreover, these clients are also present throughout the entire period, meaning that they had access to telemedicine service through 2019 and 2020. We then expand our data set to have one observation per day and client and include client fix effects in our analysis. The green line graphs the average trend for walking, driving and public transit mobility indicators as described previously. Blue dots correspond to the point estimates and confidence intervals.
Figure Appendix A.4: In-person and Telemedicine Consultations 2019-2020
Data from a Large Health Insurance Company

Note: This Figure shows a 3-week moving average of the number of in-person consultations (left y-axis) and telemedicine consultations (right y-axis) from a large health insurance company during the year 2020 (as a percentage of the number of total consultations in 2019.)
### Table Appendix A.1: Test of Parallel Trends

| Main Effects | Call Resolution |
|--------------|-----------------|
| Calls First-Time Callers | Resolved Prescription Follow-Up Referral |
| $H_0: \beta_{t1} = \beta_{t2}$ | 0.5346 | 0.4878 | 0.0962 | 0.2037 | 0.2001 |
| $\beta_{t3} = \beta_{t4} = 0$ | 0.1614 | 0.0962 | 0.2037 | 0.2001 |
| $H_0: \beta_{t9} = \beta_{t10} = 0$ | 0.0016 | 0.0052 | 0.0305 | 0.3330 | 0.2001 | 0.8127 |

Note: The table shows the p-values of Wald tests of the joint hypotheses specified in the first column, where $\beta_{tj}$ indicates the $j$–th week (with $j = 1,..,4,9,10$).

### Table Appendix A.2: Demand for Telemedicine and Spatial Mobility: Other Outcomes

| Panel A: All 2020 | $\beta_{\text{Resolved}}$ | $\beta_{\text{Prescription}}$ | $\beta_{\text{Follow-Up}}$ | $\beta_{\text{Referral}}$ |
|------------------|---------------------------|-----------------------------|---------------------------|---------------------------|
|                  | $-0.028^{***}$            | $-0.043^{***}$              | $-0.031^{***}$            | $-0.015^{***}$            |
|                  | (0.003)                   | (0.003)                     | (0.005)                   | (0.004)                   |
| Panel B: 2020 Post Week 11 | $-0.013^{***}$    | $-0.023^{***}$              | $-0.003$                  | $0.010^{**}$              |
|                  | (0.002)                   | (0.004)                     | (0.005)                   | (0.005)                   |

Note: Each column presents the Ordinary Least Squares estimate of $\alpha_1$ in equation 3 for a different outcome. The top panel present results for the full sample. The bottom panel presents results estimated using only the weeks after week 11. * statistically significant at 10%; ** at 5%; *** at 1%

### Table Appendix A.3: Health Insurance Provider’s Characteristics

|                      | Sample     | H.I. Provider | Diff.  | p.value |
|----------------------|------------|---------------|--------|---------|
| Resolved             | 62.2%      | 59.9%         | -2.3%  | 0.0004  |
| Prescription         | 58.9%      | 69.5%         | 10.6%  | 0.0000  |
| Follow-up            | 25.3%      | 32.9%         | 7.6%   | 0.0000  |
| Referral             | 8.1%       | 1.7%          | -6.4%  | 0.0000  |
| General Medicine     | 74.5%      | 82.2%         | 7.7%   | 0.0000  |
| Ob/Gyn               | 14.0%      | 13.3%         | -0.7%  | 0.1178  |
| Pediatrics           | 11.5%      | 4.5%          | -7.0%  | 0.0000  |
| Age                  | 40.3%      | 48.2%         | 7.8%   | 0.0000  |
| Male                 | 39.5%      | 48.2%         | 8.7%   | 0.0000  |
| Previously Diagnosed | 46.1%      | 56.9%         | 10.8%  | 0.0000  |

Note: The table compares the average characteristics of the outcomes of the calls, the types of calls, and the characteristics of callers for the health insurance provider (column 2), and the rest of the sample (column 1). Column 3 reports the difference between columns 1 and 2 and column 4 reports the p-value of the null the the averages in both samples are equal.