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THE POLITICAL ECONOMY OF A “MIRACLE CURE”: THE CASE OF NEBULIZED IBUPROFEN AND ITS DIFFUSION IN ARGENTINA

Sebastian Calónico
Rafael Di Tella
Juan Cruz Lopez del Valle

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ABSTRACT

We document the diffusion of nebulized ibuprofen in Argentina as a treatment for COVID-19. As the pandemic spread, this clinically unsupported drug reached thousands of patients, even some seriously ill, despite warnings by the regulator and medical societies. Detailed daily data on deliveries for all towns in one of the largest provinces suggests a role for “rational” forces in the adoption of a miracle cure: towns adopt it when neighbors that adopt it are successful in containing deaths (a learning effect), even after controlling for the average adoption of peers. Results from a survey are consistent with learning. They also reveal a large role of beliefs: subjects that are classified as “Right” are more likely adopt and to learn, while those that are “Skeptical” report an increase in their demand when primed with the regulator’s ban.

Sebastian Calónico
Columbia University
722 West 168th Street
4th Floor
New York, NY 10032
scalonico@gmail.com

Rafael Di Tella
Harvard Business School
Soldiers Field Rd
Boston, MA 02163
and NBER
rditella@hbs.edu

Juan Cruz Lopez del Valle
Boston University
Boston, MA 02215
jclopezdelvalle@gmail.com

I. Introduction

Attempts to cure people typically involve approved drugs and medical treatments. Sometimes, however, people are treated with unregulated products because unscientific claims are made by "quack doctors", normally for money. The 2020 COVID-19 pandemic offered several examples of the latter, including the case of Bolivia's president, Jeanine Añez, who appeared in public in May 2020 with a card containing chlorine dioxide around her neck, claiming it purified the air around it "eliminating virus and bacteria for a month." [1] There is a third possible category, however, that falls in between these two extremes: drugs that are explicitly banned by the regulator but that are not examples of outright fraud. These drugs may even be enthusiastically endorsed as "miraculous" by a group of health professionals, who often have minimal or no financial interest in them.[2] In this paper we study the case of one such "miracle cure," administered to thousands of COVID patients in Argentina: nebulized ibuprofen (NaIHS), a variant of the standard drug that can be directly delivered in high concentration to the lungs using easily available inhalation devices.

Originally designed to treat cystic fibrosis, researchers soon conjectured that NaIHS might be useful as a treatment for COVID patients (see Garcia, et al., 2020).[3] At the time the World Health Organization had recommended against taking standard ibuprofen to treat COVID patients, the province of Córdoba authorized the nebulized version under an unusual label: "extended compassionate use." On May 7, 2020, a leading newspaper in Argentina reported that 5 patients had "successfully" been treated with NaIHS, including two 75 years-old who were seriously ill and needed a respirator.[4] As the pandemic spread, reports of NaIHS use emerged in local and national media. Professional societies and the Argentine federal regulator (called ANMAT) soon issued explicit warnings against its use, often stressing that circulation of NaIHS across provinces was prohibited by law. Eight other provinces eventually issued similar authorizations, although use of NaIHS frequently took place outside this legal framework. For example, NaIHS was used in these 8 provinces before they had issued an "extended compassionate use" authorization, and in 10 provinces that never had one. Besides "industrial" ibuprofen, a network of compounding pharmacies produced their own variety of NaIHS which was distributed in 20 provinces. We document that, at least, 99,453 COVID

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[1] The cards appear to have cost approximately U$15 and were classified as "fraudulent" in the US by the EPA and in several Asian countries. She tested positive for COVID-19 on July 8, 2020. See, "Bolivia's president uses a 'card that blocks the virus' on sale for 15 dollars on internet," *Clarin*, May 15, 2020. An early discussion of quack doctors appears in JAMA (1906). "Snake oil" is another term for health care fraud, even if the original snake oil used in traditional Chinese medicine may have had some beneficial effects (indeed, the origin of the term is connected to the activities of one Clark Stanley, also called "The Rattlesnake King" who lost a legal case based on "misbranding": apparently the product he was selling did not contain enough snake oil; see, Gandhi, 2013).

[2] A possible example is the drug hydroxychloroquine, promoted by French medical researcher Didier Raoult. Initially receiving some support (including that of US president Donald Trump), Raoult was later accused by his peers of spreading false information about the benefits of the drug. It did have, however, FDA approval for a time.

[3] Apparently, researchers had shown that high concentrations of salt enhanced the impact of ibuprofen in reducing the infectivity of cystic fibrosis pathogens (see Muñoz, et al., 2018).

[4] See "Coronavirus in Argentina: researchers from Córdoba successfully tried a treatment with ibuprofen", *Clarin* May 7, 2020. A companion paper (Calónico, et al., 2022) studies the correlation between NaIHS consumption and health outcomes in 11 hospitals during this period.

patients were treated with one of the two versions (industrial or compounded) of nebulized ibuprofen between August 2020 and August 2022.

A natural question regarding this episode concerns how Argentines decided to adopt this drug despite the complete lack of clinical evidence on its effectiveness or safety, and against the explicit guidelines issued by regulators and professional medical societies. Specifically, was there some role for rational forces, such as learning? [5] Or did NaIHS adoption follow simpler rules such as mimicking what peers were doing? Was there a role for political beliefs? [6]

We tackle these questions using two data sets. The first is a panel of most towns in the second largest province of Argentina (the province of Córdoba; 491 towns accounting for 99.67% of its population) and combines data on NaIHS deliveries to each town with official data on the evolution of the pandemic (deaths and cases). We focus on the role of the neighbors' decision to adopt, which we interpret as a peer effect, and on a town's relative performance (in terms of deaths from COVID-19) after they adopt NaIHS, which we interpret as a more sophisticated learning mechanism. The second data set is a survey of 4,861 individuals living in Córdoba and three other big districts (the provinces of Neuquén and Buenos Aires, as well as the city of Buenos Aires). It collects their views on NaIHS, their beliefs on a range of issues, as well as a set of demographics. Importantly, the survey randomly exposes respondents to information describing the use of NaIHS despite the lack of a clinical trial (Treatment 1), information regarding the widespread use of NaIHS (Treatment 2), information regarding both the widespread use of NaIHS and of its apparent effectiveness (Treatment 3). A fourth treatment exposes subjects both to information regarding its existence (as in Treatment 1) and to the warnings against its use (issued by regulators and professional groups).

We document that 184 towns (37% of our sample) adopted NaIHS, with 64 of them (13%) eventually discontinuing its use. We find that towns that are far away from the provincial capital, with fewer college graduates and where the opposition, center-right presidential candidate (Mauricio Macri) got the most votes in the 2019 national elections are more likely to adopt NaIHS. Exploiting the high frequency of the deliveries data in our panel, we find that towns are more likely to adopt when other

[5] We do not focus on the regulatory decisions, but a tradition going back to Peltzman (1973) focuses on the costs of requiring proof of efficacy for new drug approvals by the FDA (see, for example, Philipson and Sun, 2008). Mulligan (2021) revisits the approach during the pandemic and argues that "FDA regulation is incomplete without accounting for substitution toward potentially unsafe and ineffective treatments" that fall outside its jurisdiction. There is growing interest in understanding how scientific information is absorbed by doctors and their patients. Depalo, et al. (2019) is a recent study of doctors and patient decisions before and after the diffusion of the results of a randomized evaluation of the side effects associated with taking statin medication.

[6] The connection to political beliefs is suggested by US president Donald Trump's endorsement of hydroxicloroquine. On March 19th, Trump suggested that this drug, which was already approved by the FDA for the treatment of malaria, could be used against COVID-19. On March 20th, the director of the National Institute of Allergy and Infectious Diseases, Anthony Fauci, corrected him. On March 24th a man in Arizona died after taking a form of chloroquine that is used to clean fish tanks. On March 28th the FDA granted Emergency Use status for Covid treatment to hydroxychloroquine. On April 16th a clinical trial being carried in Brazil had to be stopped as some patients developed a cardiac condition. The authors of the studies received threats and Eduardo Bolsonaro, son of Brazil's president, described it as "a fake study aimed at demonizing the drug". On June 15th the FDA revoked the Emergency Use authorization.

towns that have adopted NaIHS do better (in terms of fewer COVID-19 deaths) even after controlling for average adoption amongst "peers" (defined as geographic neighbors).

Our survey data reveals that almost 36% of those in our sample had either taken NaIHS themselves or had a family member that had. Another 41% knew somebody that had been treated with NaIHS, for a total of 77% exposure to NaIHS. It also reveals interesting correlations. For example, those on the ideological right, those with lower educational attainment and those outside the richest city in our sample (Buenos Aires) express a preference for NaIHS. The same is true amongst those that accept a conspiratorial account of the suspension of hydroxychloroquine as a cure for COVID-19 in France, those who report low trust (particularly in science and in business), those that have consumed non-traditional medicine and those that are more religious. Exploiting our experimental design, we find a large positive impact of priming with NaIHS popularity and perceived effectiveness on reported preference for NaIHS.

In contrast to our panel data on deliveries, our survey allows us to study heterogenous treatment effects in some detail. Our estimates of the impact of learning in the survey are driven by right-leaning respondents. Indeed, there are no detectable learning effects (with negative point estimates) in the center and left leaning sub-samples. All the changes in our measure of preference for NaIHS amongst center and left leaning subjects are caused by the popularity treatment which we interpret as a peer effect.

Finally, we also find a large, negative effect of informing respondents of the fact that regulators have not approved its use on reported preference for NaIHS. Again, we find differences across ideological groups, with the smallest reduction found in the sub-sample of respondents that are ideologically on the right. One sub-group is particular in this regard: skeptics *increase* their preference for NaIHS once they are reminded of the negative position of the regulator and professional groups.

Our approach borrows from a large literature on technology adoption and learning in economics, even if the fact that we don't know if NaIHS is a "superior" technology (and it is illegal) violates a central assumption of prior work in the tradition of Griliches (1957). Closest to our paper is work on treatments with uncertain effectiveness by Cutler, Skinner, Stern & Wennberg (2019). They study regional variations in health care expenditures and how they are related to the presence of physicians characterized by beliefs that are unsupported by clinical evidence (whom they call "cowboy doctors"). Their presence can explain 35% of end-of-life Medicare expenditures and 12% of Medicare expenditures overall. Interestingly, they find that the absence of a financial penalty, rather than the presence of financial incentives, mostly accounts for "cowboy" doctors' actions. In the case of NaIHS, an important factor in its spread appears to have been the enthusiastic public support of some doctors.[7]

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[7] See, for example, the testimony reported in "Covid patients in Oran improved dramatically with NaIHS: The drug was administered over two weeks to Covid-19 patients on a respirator, who were released on the weekend," *La Gaceta de Salta*, September 21, 2020. A basic challenge in interpreting the apparent physician preference for NaIHS is that their decisions are sometimes viewed as suboptimal. In their study of the efficiency in healthcare provision in the US, Chandra & Staiger (2020) find that smaller hospitals are particularly prone to have inaccurate beliefs about the effectiveness of their

Prior work has documented variation in treatment propensity (and outcomes) across hospitals in the US, even after controlling for patient risk (see, for example, Skinner, 2011 and Finkelstein et al., 2016). An interesting paper by Chandra & Staiger (2020) studies data on patients that suffered a heart attack and find that hospitals overuse the main treatment (reperfusion therapy) to the point that one group of patients is in fact harmed by the treatment. Currie & MacLeod (2020) study doctor's decisions to experiment with treatments for depression and to sometimes violate "loose professional guidelines." Using patient claims data, they find that among skilled doctors, the use of a broader portfolio of drugs predicts better patient outcomes, except in those cases where their decisions violate these guidelines. More recently, Agha & Zeltzer (2022) document the diffusion of a new generation of "blood thinners" across networks of doctors in the US. They find that payments by pharmaceutical companies increase the prescriptions of anticoagulant drugs by targeted doctors and their peers to both recommended and contraindicated patients.[8]

There is a long tradition, much of it in political science, of studying the diffusion of policies with uncertain benefits (e.g., Walker, 1969, Volden, et al., 2008, dellaVigna and Kim, 2022). Some of it focuses on drug approval at the FDA as a process of bureaucratic learning (Carpenter, 2002). Outside a health context, an important paper for us is Buera, Monge & Primiceri (2011), who study how countries learn about the growth effects of market-oriented economic policies. In large part, the role of "ideologues" pushing for free markets is not dissimilar to over-enthusiastic doctors with strong beliefs about clinically unproven drugs like NaIHS. A large literature in development, that goes back to Foster & Rosenzweig (1995), studies how farmers learn about new technologies. Conley & Udry (2010) study pineapple production in Ghana where there is uncertainty about the productivity of combining inputs, concluding that farmers adjust their use of fertilizer when neighboring farmers that made similar decisions do badly. They also find that farmers incorporate information from those that make different decisions to them and are unexpectedly successful.[9]

Finally, our paper is related to work on political economy. Alsan & Wannamaker (2018) show that disclosure of medical mistreatment for syphilis of black participants in the Tuskegee Study was

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treatments, possibly due to a "general lack of systematic performance feedback and small samples." (see, also, Currie & MacLeod, 2017).

[8] There is substantial prior work on the diffusion of health-related products, even if it doesn't involve overuse or violation of professional guidelines. Chandra et al. (2014) present evidence of higher quality hospitals adopting new medical technology earlier. Skinner & Staiger (2015) show how hospitals quickly adopting innovations have better outcomes for their patients. An important early strand emphasizes peer effects in health care decisions (Coleman, et al. 1957). Recent examples in this tradition include Donohue et al. (2018), Agha & Molitor (2018) and Chan (2021). Finkelstein et al. (2016) is a study that can separate the role of supply and demand factors to study the causes of variation in health care use by Medicare beneficiaries. Doyle et al., (2015) find that quasi-random allocation to higher cost hospitals treating patients aggressively yield better outcomes.

[9] See also Bandiera & Rasul, (2006). Hanna, et al., (2016) study the more unusual case of technology disadoption. Bold, et al. (2017) find that the quality of fertilizers and hybrid seeds sold in local markets in two maize-growing regions of Uganda is low on average, which can explain low adoption rates. They estimate that the learning environment does not allow small farmers to distinguish authentic inputs from those that have somewhat lower quality, reducing the incentive for sellers to use reputation as differentiation. Work in this tradition use different strategies to separate learning from peer effects in the context of adoption of health technologies (examples are Munshi & Myaux, 2006, on fertility; Kremer & Miguel, 2007, on deworming and Oster & Thornton, 2012 on menstrual cups).

associated with medical mistrust, mortality and lower demand for physician services. During the pandemic vaccine hesitancy emerged as a major concern (See Coconel Group, 2020). Evidence emerged that ideology was strongly associated with a host of relevant factors, including perceptions of risk (Barrios & Hochberg, 2020) and attempts to avoid the virus through mask use, social distance, etc. (see Allcott, et al., 2020, Grossman, et al, 2020, and Milosh, et al., 2020). Closer to this paper is Galasso, et al., (2022), who demonstrate that messages with information about the benefits of vaccines (for example in avoiding infecting others or in protecting the economy) were effective in increasing vaccination rates even amongst respondents who had expressed anti-vaccine views.[10]

More generally, political polarization and populist beliefs have been linked to attitudes towards expertise and science (for reviews, see Iyengar et al., 2019, Brodeur, et al. 2021, and Guriev & Papaioannou, 2022). Albornoz, et al. (2022) show that people's intended compliance with different recommendations to reduce exposure is reduced when it is attributed to experts. The evidence in Lewandowsky, et al. (2013), for example, is suggestive of paranoid beliefs predicting the rejection of all propositions presented as scientific, in contrast to conservative beliefs, which are predicted to reject only scientific findings that are associated with greater regulation (for a model where paranoid preferences lead to a rejection of expertise, see Di Tella & Rotemberg, 2019). Bellodi, Morelli & Vannoni (2021) document how populist mayors in Italy replace qualified civil servants with non-experts hurting government performance.

In the next section we discuss the regulatory context and timeline. Section III presents the data, empirical strategy, and results for NaIHS adoption across our panel of 491 towns during the initial phase of the pandemic. Section IV presents our survey data, empirical strategy, and results on NaIHS preference in our sample of 4,861 individuals. Section V discusses the results and concludes.

II. Timeline, Regulatory Context and Non-Industrial NaIHS

II.a. *Timeline and Regulation: Basic Data on the spread of Industrial NaIHS*

On March 3, 2020, the first COVID-19 case was reported in Argentina. The government closed all schools on March 16 and mandated a full lockdown on March 20. It involved extreme measures, with people not authorized to leave their homes except in emergencies or to buy food. By early June, there had been more than 93,000 people detained for transit without a permit (for a description of the extreme nature of Argentina's confinement policies, see Gibbons, Murphy & Rossi, 2021). Vaccines reached health personnel in Argentina during February-March 2021.

[10] For work on the use of traditional medicine in Central Africa, see Lowes & Montero (2019). On the demand for traditional healers in Africa, see Leonard (2003). On alternative medicine, see Bodeker & Kronenberg (2002). A fascinating description of a failed attempt to demonstrate the effectiveness of homeopathy through an early version of a randomized controlled trial is Stolberg (2006).

The first report of NaIHS use appeared on May 15, 2020 (see our footnote 4 above). At the time, the World Health Organization had advised against the use of traditional ibuprofen (e.g., see Day, 2020).[11] *Química Luar,* a small pharmaceutical company in the province of Córdoba, was in the process of obtaining regulatory approval to use NaIHS to treat cystic fibrosis, when researchers speculated that it could be used as a treatment for COVID-19 (see García et al., 2020). Treating COVID-19 with NaIHS consists in directly delivering a low dose of ibuprofen in a hypertonic saline formulation to the lungs using widely available inhalation devices three times per day.

The federal regulatory agency (*Administración Nacional de Medicamentos, Alimentos y Teconología Médica, ANMAT*) did not approve the use of NaIHS during our sample period.[12] On April 2, 2020, however, the company obtained an authorization by the provincial government of Córdoba under an unusual legal category: "extended compassionate use." The standard authorization (simply called compassionate use) of a drug only allows for limited use in extreme circumstances and requires both that patients explicitly request it and that the treatments are authorized in another country or that clinical trials are under way.[13] We are unaware of extended compassionate use authorizations in other cases. One practical problem raised by the provincial authorities appears to have been how to nebulize patients without spreading the virus, something that was "solved" using a "helmet" (but it is unclear how widespread was its use; see Figure 1).

The *ANMAT*, as well as two professional societies issued warnings against its use. On August 24, 2020, *ANMAT* clarified that there was no clinical trial under way and that transit across provinces of unauthorized products was prohibited.[14] Still, reports of COVID-19 patients treated with NaIHS outside of Córdoba emerged in local and national media. In 20 out of the remaining 23 provinces,

[11] Later, the WHO withdrew its reservations (Kragholm et al., 2021).

[12] Regulatory delay in the approval of new drugs is a standard concern (Peltzman 1973; Budish, Williams, and Roin 2015). In advanced countries, approval often marks the end of an "exhaustive journey through basic research, discovery of the medicine, preclinical development tests (and) increasingly complicated clinical trials with humans" (Corr and Williams, 2009). While there is some flexibility introduced for off-label, repurposed and compounding drugs, urgent patient needs, such as those that emerged during the pandemic, put a strain on this process. In Argentina, however, *ANMAT*, adopted a "simplified mechanism" for critical products during the pandemic. Relaxing standards for the use of drugs/vaccines was at the forefront of policy discussions in the US, including the off-label use of existing drugs (see Kalil, 2020) and repurposing off-patent drugs (see Conti, et al., 2020). Chandra et al. (2014) discusses the diffusion of new medical technologies in the US following approval of the regulator (see also Berger et al., 2021). For a model where firm costs and experimental history of the product affect the credibility of a new submission, see Carpenter and Ting (2007).

[13] One drug that was in this category was Gilead's laboratory Remdisivir, although in Argentina it was hard to obtain and prohibitively expensive. In the US patients may access drugs that are not yet FDA approved by participating in clinical trials controlled by drug manufacturers. In 2018 a "Right to try" law formalized the conditions for people outside clinical trials to access unapproved drugs. See GAO (2019).

[14] See the communications on NaIHS by *ANMAT*, the Argentine society of infectiology (*Sociedad Argentina de Infectología, SADI*) and the Argentine society of intensive care (*Sociedad Argentina de Terapia Intensiva, SATI*). As an example, the *ANMAT* communication for August 24th, 2020 reads, "In reference to the authorization for a clinical trial of the product LUARPROFENO for the treatment of COVID-19, this National Administration informs **that no procedure has been initiated** for the evaluation of this protocol. Also, it should be emphasized that, not being authorized at the national level, said product **does not have authorization for inter jurisdictional transit**." *Administración Nacional de Medicamentos, Alimentos y Tecnología Médica* (ANMAT). Emphasis in the original. The intention to do a clinical trial for COVID-19 was registered at the website clinicaltrials.gov on May 11th, 2020.

NaIHS appears to have been consumed without a proper authorization in place, either because that province never issued an "extended compassionate use" authorization or because there are reports of its use before such authorizations were issued.

A key aspect of our paper is the complete absence of clinical evidence on the effectiveness of NaIHS to treat COVID-19, both during our sample period and to this date. The *ANMAT* only authorized the phase II in August 2021, after the end of the second wave. An early discussion appears in García et al. (2020) and Salva et al. (2021). In a companion paper we study clinical data on 5,146 patients hospitalized in 11 health centers, some of them seriously ill (Calónico, et al., 2022). It documents a negative correlation between NaIHS consumption and deaths, controlling for a series of confounds, in several -but not all- empirical specifications, something that is at least consistent with the initial enthusiasm of the doctors recommending it. None of these papers present evidence on safety and side-effects.

As the number of COVID cases in Córdoba begun to rise sharply in July 2020, several towns in the south of the province reached the limit of hospital capacity. NaIHS then began to be used on patients in some private clinics. Soon all health facilities of two medium sized cities (Villa María and Río Cuarto) were at full utilization and had to limit the number of patients they could accept from neighboring towns. At that point, NaIHS begun to be used outside hospital settings. Through a personal connection with *Química Luar*, the mayor of Arroyo Cabral, a small town along route 158 which connects these two towns, obtained NaIHS and began to administer it in early September. It appears that he was instrumental in putting *Química Luar* in contact with other towns (see, Kalayan, 2022). The health strategy evolved: whereas up to then NaIHS was used on hospital patients that typically were already 6-7 days into their struggle with COVID, smaller towns with less infrastructure and simpler health facilities begun administering it earlier (inside the initial 6-7 days) to individuals with high risk of complications. The mayor of Arroyo Cabral was affiliated with the center-right coalition. The large public hospitals in the capital city of Córdoba were relatively late adopters.

Our data reveals that up until August 2022 a total of 508,450 doses of industrial ibuprofen were delivered, of which 347,450 were delivered in the province of Córdoba. Using an average of 8 doses per patient for a full treatment used in the non-critical cases, then approximately 63,556 COVID patients were treated with industrial NaIHS (of which 43,431 were in Córdoba).

In terms of traditional regulatory categories, the use of NaIHS in the province of Córdoba is closest to an off-label use in the US.[15] The company claims the changes are so extensive that make it a new, unique drug (see *Química Luar*'s communication, 2020). One must add the explicit ruling by the national regulatory agency (*ANMAT*) against it and the novelty of the "extended compassionate use"

[15] See "Understanding Unapproved Use of Approved Drugs 'Off Label'" in the FDA website. It explains, for example, when it is "used for a disease or medical condition that it is not approved to treat … given in a different way, such as when a drug is approved as a capsule, but it is given instead in an oral solution … given in a different dose." Using representative data for the US from 2001, Radley, et al. (2006) estimates that 21% of the use of 160 commonly used medications were off label. Most had little or no-scientific support. During the pandemic off-label therapies used include remdesivir, hydroxychloroquine, azithromycin and lopinavir-ritonavir). See Kalil, (2020). One concern is the presence of adverse effects ("Overall, there are 2-3 times as many adverse events with off-label use as on-label prescriptions and when you work this out, it comes to 35,000-45,000 deaths per year associated with the practice;" Persidis, 2015).

regulatory category issued by the provincial authorities (which was unprecedented, and we know of no other examples outside of Argentina). Consumption of industrial NaIHS outside of Córdoba faces the extra challenge of the lack of an "extended compassionate use" approval in many provinces as well as explaining how NaIHS produced in Córdoba got there legally given that transit across provinces was not allowed.

II.b. Distribution of Compounded Ibuprofen

A network of pharmacies produced a (non-industrial) variant of NaIHS.[16] In August 2020, a compounding pharmacy in San Nicolas, a medium size city with a population of 162,000 in the Province of Buenos Aires, begun dispensing a variation of nebulized ibuprofen. A pharmacist modified the formula using less salt in order to simplify its administration as well as its production in a non-industrial setting. He belonged to a large network of 605 compounding pharmacies, which soon started distributing non-industrial NaIHS, apparently for free, under the sole condition of it being prescribed by a physician. By September (one month later), affiliated pharmacies had already distributed it in 9 out of 24 of Argentina's provinces. One reason for its relatively fast spread was that compounding pharmacies were local, so the product did not need to cross provincial limits. On October 14th, 2020, the pharmacist announced, "we don't know of a single patient that did not respond positively." [17]

An interesting case is the province of Santa Cruz, where the governor refused to issue a compassionate use authorization for industrial NaIHS. During October 2020, the political party in the opposition insisted, arguing that NaIHS should have the same status as convalescent plasma because "it also lacks scientific support, nevertheless is being used in the province with good results."[18] The province's medical society issued a public communication explaining that a survey of registered physicians resulted in strong support for allowing NaIHS in the province (with 97 members in favor, 1 against and 3 refusing to answer) and urging the government, including the health minister (who was a member of the medical society), to approve it. Over the last weeks of October, one physician in the town of Caleta Olivia defied the restrictions and started prescribing compounded NaIHS "regardless

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[16] They argued that "it is an orphan medicine since the formula cannot be found in the market." See, "Pharmacists offer Nebulized Ibuprofen for free," *Diario El Zonda*, October 27, 2020. Compounding refers to the pharmaceutical practice of adapting approved drugs for patients with special needs (e.g., when they have an allergy or need a different dose). The FDA defines it as a drug prescribed for rare conditions (fewer than 200,000 people) or one which will not be profitable in the 7 years following FDA approval. However, compounding drugs do not have to get FDA approval and regulations for compounding pharmacies differ by state. There are complaints of a legal vacuum (see "State of Disarray", *U.S. House of Representatives*, April 12, 2013): in 2012, a meningitis outbreak caused by epidural steroid injections provided by the New England Compounding Center ended with around 800 contagions and 100 deaths (see "How Back Pain Turned Deadly", *New York Times,* November 17, 2012).

[17] Interestingly, there are explicit concerns about "miracle drugs" in the regulation of pharmacies. Article 32, of law 17.565, which regulates pharmacies, states "[...] professionals that exercise pharmacy are likewise forbidden from a) Announcing or issuing drugs that have a secret or mysterious composition; b) Announcing and issuing therapeutic agents attributing them infallible effects or extraordinary or that offer to radically cure any illness; c) Applying in their private practice procedures that have not been presented or considered or approved at university centers or that are scientifically recognized in the country; and d) Announcing on any media drugs or specialties not recognized by the health authority."

[18] The use of plasma was allowed by ANMAT and a national campaign to donate plasma was launched while there was a clinical trial underway (PLASM-AR). It was suspended on October 3, 2020 when the results came in negative.

of the personal consequences that I will face." Perhaps because of this, the town of Caleta Olivia is the town where more compounded NaIHS was produced according to our data: 79,600 doses (if 8 doses are required to treat each patient, this implies that 9,950 patients received compounded NaIHS originating in Caleta Olivia).

By the end of October, COVID-19 patients in 14 out of the 24 provinces received compounded NaIHS. Eventually, by February 2021, 20 out of the 24 would be in this category. Out of a total of 605 pharmacies in the network, the information supplied to us reveals that 134 had compounded NaIHS at least once following a physician's prescription. We have aggregate data on 86 of these pharmacies, which prescribed 287,170 doses after receiving prescriptions filled by 2,464 physicians. Assuming 8 doses on average, we estimate a total of 35,896 patients were treated with compounded NaIHS. For 31 of those 86 pharmacies we have detailed data, and we observe that a large proportion of physicians repeat their prescriptions (for example, of the 64 physicians that prescribe compounded NaIHS in September 2020, 50% also prescribe it in later months).

We estimate that 795,620 doses of industrial or compounded ibuprofen were used by August 2022, implying that at least 99,453 COVID patients were treated with one of these versions (using an average of 8 doses per patient). This estimate is a lower bound because we only have data on compounding NaIHS deliveries (287,170 doses) until the end of February 2021 and this uses data for only 86 (out of the 134) compounding pharmacies which were operating at the time.

III. Adoption of Industrial NaIHS in a Panel of Towns

Our main data in this section comes from the province of Córdoba, the place where industrial NaIHS was produced, and thus consumption did not require transit across provinces. Also, this is where NaIHS was first used (and where most of the industrial NaIHS was used - over 68% of the total). It is also where our data on compounded NaIHS shows the least penetration (with only one compounding pharmacy operating in the province). Córdoba is one of the richest provinces, with reasonable state capacity, with daily data on COVID cases and deaths available at the town level.

Figure 2 shows the evolution of the main variables for our sample of towns in Córdoba over the 62 weeks in our study. Panel (a) shows the number of NaIHS doses delivered, while Panels (b) and (c) show the evolution of COVID cases and deaths, respectively. The time diffusion of industrial NaIHS in the Córdoba province is further described in Figure 3, where we classify adopter towns (a town where NaIHS begins to be used) into desadopters (if adoption was temporary) and forever-adopters. Figure 4 splits the data along political lines. NaIHS adoption follows the classical Griliches (1957) S-curve adoption pattern. The S-curve pattern holds within political affiliation, (for recent evidence on spatial heterogeneity in "universalist" beliefs as a predictor of geographic variation in political outcomes- stronger than traditional economic variables such as income or education-, see

Enke et al., 2023).[19] Finally, Figure 5 shows the geographic diffusion of industrial NaIHS in the Córdoba province.

III. a. Data Description:

Our study of NaIHS adoption across a daily panel of 491 towns of the province of Córdoba from August 2020 to November 2021 combines three sources of town-level data: (i) official daily reports of COVID-19 cases and deaths, (ii) information on the date and geographic location of the deliveries of industrial NaIHS, and (iii) general cross-sectional data, including political, geographic, and demographic information. Official data on COVID-19 cases and deaths at the town level was obtained from the Center of Emergency Operations (C.O.E.), an interdisciplinary effort by the province designed to centralize information and decision making during the pandemic in the Córdoba province. Data on deliveries was provided by *Química Luar*. Cross-sectional data was obtained from different sources: (iii.a) 2019's presidential elections results for each town were obtained from RStudio package polAr,[20] (iii.b) geolocation data for each town was obtained from Córdoba's General Direction of Statistics and Census and for each provincial hospital from Córdoba's Infrastructure of Spatial Data (IDECOR) (iii.c) data on computer and mobile phone usage, education and population was obtained from Argentina's 2010 national census, available at the National Institute of Statistics and Census.

We have data on COVID-19 cases and deaths from April 30th, 2020, to March 14th, 2022, and we have NaIHS deliveries data from 25th August 2020[21] to August 1st, 2022. Our potential sample period is the overlap between these two datasets: between 25th August 2020 to March 14th, 2022. However, we restrict attention to data before November 4th, 2021, the day before the first day of the first week without deaths in our sample period. By then, vaccines had become widely available and there is a drastic drop in COVID deaths (0.018 deaths per case during the sample period we use vs 0.002 in the period we discard) and NaIHS usage (0.568 doses per case vs 0.103). Hence, our final sample period is the 62 weeks that go from 25th August 2020 to November 4th, 2021.[22]

We start from the universe of 521 towns as measured by the national census and drop 13 towns that have less than 20 inhabitants. We also drop 1 town with no geolocation data. Political data is directly

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[19] Skinner and Staiger (2007) report on the debate between Griliches, who emphasized the role of economic incentives in the diffusion, and sociologists such as Rogers (1962), who emphasized the role of networks and the characteristics of decision makers. They point out that, even if Griliches (1957) ultimately recognized the potential importance of sociological factors, work in the two disciplines has showed little cross fertilization.

[20] The original data, which is at the voting school-circuit level, was aggregated at the town level using the report on the 2019 presidential elections provided by the National Electoral Direction which depends on the Judicial Branch.

[21] These are the first and last delivery we observe in our data *within the province of Córdoba*. The first delivery we observe in our data is August 11th to the province of Jujuy and the last one August 3rd to the province of Buenos Aires.

[22] By November 2021, 80% of the population had at least one dose of the vaccine and 60% had received two doses. Results are robust to extending the period of analysis to March 14, 2022 (see Table A1 in Appendix A1).

available for 444 towns. For 47 of the remaining 63 towns, we can impute political data from a neighboring area.[23] Our final sample includes 491 towns where 99.67% of Córdoba's population lives.

Main Constructed Variables

To capture political preferences, we exploit the difference between the percentage of votes in each town for the 2019 presidential election between the opposition (center-right) candidate Mauricio Macri and the center-left government candidate, Alberto Fernandez. *Right* is a dummy that takes the value of one when the difference is larger than 0%. *Distance to Córdoba* and *Distance to Hospital* are expressed in kilometers (and calculated as bird's eye). *Computers, Mobile Phones* and *College* are expressed as percentage of the population. Córdoba's constitution classifies towns as a *Commune* whenever it has less than 2,000 residents, a *Municipality* when it has between 1,000 and 10,000 and a *City* when it has above 10,000. In the cross-sectional analysis, we use *Cumulative Cases* and *Cumulative Deaths* taken at the end of our sample period, the first week of November 2021.

We have data on NaIHS deliveries but not on consumption. To approximate it we construct a time-varying-town-specific dummy variable in the following way: whenever a town ordered NaIHS for the first time, the dummy takes the value one. If the town ordered NaIHS more than once, then the dummy never turns off to zero. If the town ordered NaIHS only once, there are two plausible scenarios: they were unhappy with it or they didn't need more. If the town did not order NaIHS again despite having reached a high number of deaths the dummy is switched to zero (this is defined as the median number of deaths per capita that towns had when they ordered a second time, which turns out to be 16.35 per 10,000 inhabitants). If the town did not reach the high number of deaths threshold, we leave the dummy at 1, even when they did not order NaIHS again. We call this variable *NaIHS*, which is the outcome used in our panel analysis. The cross-section analysis uses a variant of this information: towns for which *NaIHS* takes the value of one for at least one period are *Adopters*. Their complement, towns for which *NaIHS* never got a value of one, are *Non-Adopters*. Within *Adopters*, towns for which *NaIHS* never takes the value of zero again are *Forever-Adopters*. Their complement, towns for which *NaIHS* takes the value of zero again, are *Desadopters*. Also, within *Adopters*, towns for which *NaIHS* got the value of one during the first seven weeks of our sample are *Early-Adopters*. Their complement, towns for which *NaIHS* got the value of one after the first two months, are *Late-Adopters*.

III. b. Empirical Strategy:

Our empirical strategy follows Buera, et al., (2011) and estimates regressions of the form:

$$\begin{aligned} NaIHS_{i,t} = \phi_i + \phi_t + \phi_1\, NaIHS_{i,t-1} + \phi_2 \left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1 \right) \\ + \phi_3 \left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0 \right) + \phi_4\, \overline{NaIHS}_{n(i),t-1} \end{aligned}$$

[23] Missing towns are of three types: those that are a private neighborhood, those that do not have a school apt for voting, and those that depend administratively on another town. They account for 0.39% of Córdoba's population.

where $NaIHS_{i,t}$ is town's i adoption of NaIHS in period t, ϕ_i are geographic level fixed-effects, ϕ_t are period fixed-effects, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ is a weighted average of COVID deaths per capita of towns i neighbors $n(i)$ that were using NaIHS at $t-1$ (where the neighbors $n(i)$ are all towns in the province weighted by their population and distance from i), $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ is a weighted average of COVID deaths per capita of towns i neighbors $n(i)$ that were not using NaIHS at $t-1$, and $\overline{NaIHS}_{n(i),t-1}$ is a weighted average of the number of i neighbors $n(i)$ that were using NaIHS at $t-1$. Persistence of policies, implied for example by persistent beliefs that follow Bayesian updating as in Buera, et al. (2011), suggest that $\phi_1 > 0$. Learning effects $\phi_2 < 0$ and $\phi_3 > 0$ respectively and peer effects $\phi_4 > 0$. In the main specification weights increase linearly with population, decay exponentially with distance and the daily data is collapsed into week periods.

As in Conley & Udry (2010), identification comes from the timing of bouts of new information. In other words, we exploit the timing of NaIHS COVID related deaths in towns as opportunities for information transmission about the effectiveness of each town's strategy to fight the pandemic. Since towns had a limited set of options (especially during the first wave), and the topic was salient for all the inhabitants of each town, we assume that NaIHS adoption was known outside the town, particularly amongst close neighbors. Thus, conditioning on adoption offers information regarding the effectiveness of each town's strategy. Our approach then is to see if towns react to these information shocks in a way that is consistent with learning. Note that we can condition on average adoption of NaIHS amongst a town's neighbors, so we can plausibly separate peer effects from learning, a strategy that is also followed in Buera, et al. (2011).

Conley & Udry (2010) quote Moffitt (2001) who describes the need of a policy that "changes the fundamentals for a subset of the population in a group in an attempt to influence the outcomes of the others in the group". In their case this is dictated by the exogenous natural cycle of pineapple planting, whereas we rely on the high frequency of our data. Towns receive information about policies and outcomes from other towns which can be argued to come as a surprise at this granular frequency (what is happening in other towns and when this becomes known is arguably, at this high frequency, orthogonal to any other motive behind a town's NaIHS demand). Of course, the argument becomes less credible the longer the periods into which we collapse the daily data, so there is a trade-off with more noisy daily data. Moreover, note that Manski's (1993) reflection problem is a perversive threat in the social interactions literature that is broken when each town has a different set of "neighbors." We control directly and indirectly for correlated policies with the $\overline{NaIHS}_{n(i),t-1}$ term and with town's i own cases and deaths at the period, respectively.[24]

[24] This control can be interpreted as Conley & Udry's (2010) "growing conditions". They argue that we can be observing social interactions effects simply because the underlying conditions of adoption are correlated between neighbors (instead of controlling for "growing pineapple conditions," we control for "growing deaths conditions"). Buera et al. (2011) mention that their model belongs to a family of binary choice that possess non-linearities that make identification more plausible. See also Brock & Durlauf (2001).

III. c. Results:

Table 2 shows cross-sectional correlations of NaIHS adoption status for our final sample of 491 towns. There is a positive association between *Right* and adopting NaIHS. Distance to the province's capital is weakly correlated with NaIHS, perhaps suggesting distant towns willingness to experiment, less oversight from the provincial power or because there are differences in skill.[25] More modern units typically adopt new technologies faster (e.g., Skinner & Staiger 2007), so we include *Computers*, *Mobile Phones* and *College* as controls. Municipalities, and cities, have a higher probability of adopting NaIHS, relative to smaller towns. Cumulative COVID cases and deaths (at the end of our sample period) do not predict adoption of NaIHS. To get a sense of the magnitude of these effects, the proportion of adopters jumps from 31% to 39% when the measure of a town's political ideology goes from left to right. At the bottom of this table, we report Moran's I tests for spatial autocorrelation of residuals. A value of 1 means perfect spatial clustering of the residuals, a value of -1 perfect spatial dispersion and a value of 0 perfect spatial randomness. We can reject the null of no spatial autocorrelation across towns in our model of adoption, suggesting there is a component of spatial distance that remains to be explained, which we explore in the panel specifications.

The second and third columns of Table 2 analyze adoption status within *Adopters*. Column 2 compares *Forever-Adopters* against *Desadopters*. Column 3 compares *Early-Adopters* against *Late-Adopters*. *Right* (weakly) and distance from Córdoba are correlated with early adoption of NaIHS.

Learning and Peer Effects in the Diffusion of NaIHS

The first column of Table 3 presents our main specification without geographic level fixed-effects. The second column adds department fixed effects (there are 26 departments). The third column replaces department fixed effects with town fixed effects. The fourth column adds town specific time trends to the third column. Coefficients appear stable across specifications and adoption is persistent (first line). The regressions estimate learning (second and third lines) controlling for peer effects (fourth line). We find significant learning effects, mainly as the result of information coming from the performance of adopters (second line).

A town's likelihood of adoption in the short run drops from 23% to 21.30% when our measure of information moves from the bottom to the top decile in terms of deaths (i.e., when the seven days weighted average of deaths amongst neighbors that adopt NaIHS is in the top rather than in the bottom decile and the rest of the variables are at their mean level).[26] Using the estimate from column 4, the long run effect is almost 5 times the short run effect.

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[25] Note that we control for distance to 28 provincial hospitals and include controls for education. Chan, Gentzkow & Yu (2022) emphasize the role of radiologists' skill in explaining differences in pneumonia diagnostic decisions. On the diffusion of disruptive technologies in the US see Bloom, et al., (2021).

[26] The Appendix provides several robustness checks. Table A2 uses a continuous version of *NaIHS*. Table A3 (a) and Table A3 (b) uses a sample of small towns and information on the institutions receiving the deliveries. Table A4 estimates Table 3 using 5 days as the unit for each period. Table A5 uses a socio-cultural definition of neighbors.

Heterogeneity in Learning

Table 4 repeats Table 3 but interacting the learning and peer effects variables with the dummy *Right*. The results suggest that learning is not driven by towns classified as *Right* (the coefficient of $Right_i \times \left(\overline{Deaths_{n(i),t-1}} \mid NaIHS_{n(i),t-1} = 1\right)$ is not statistically significant different from zero).

IV. NaIHS Preference in a Survey of Individuals

IV.a. Data Description:

During 2022, we engaged a private company to conduct an online survey with an experimental component based on priming. It is hard to pay subjects for large scale experimental studies in Argentina and this company had some experience recruiting subjects through its own Facebook group and newly targeted Facebook ads, which specified that participants must be over 18 years of age. Subjects first read a message that invited them to participate in a survey about the pandemic in Argentina, informing them about the length of the survey and the prize. As an incentive, respondents who completed the survey participated in a lottery for a voucher of $80,000 Argentinean pesos (~US$250, one and a half Argentinean minimum wages at the time). This ensured a high response rate as it is four times the value of the voucher that the company usually employs. The initial prompt also assured participants they would remain anonymous (only the winner of the voucher lottery would be identified, but without connecting him/her to the answers of the survey) and elicited their consent. The company administered the survey through the software *QuestionPro,* which was able to check the IP address to avoid subjects taking the survey twice.

The focus was the province of Córdoba, where the company had a target of 1,200 answers distributed according to the size of the town: a third of the sample was to be recruited from small towns (less than 10,000 inhabitants), another third from towns of intermediate size (between 10,000 and 100,000 inhabitants) and the remaining third from towns with population higher than 100,000 inhabitants. For comparison, we asked that the rest of the survey target the Province of Buenos Aires, (800 cases came from the metropolitan area of the city of Buenos Aires, 800 cases came from towns with population above 200,000 and 600 cases from towns below 200,000 inhabitants), the province of Neuquén (1,000 cases) and from the city of Buenos Aires (1,2000 cases). Note that the city of Buenos Aires is the richest in the country, with the best health care infrastructure and where use of NaIHS was very low. The starting date was September 16, 2022, and the final answers were recorded on December 12, 2022. We collected a total of 5,005 responses, from which we discarded 89 cases (1.78%) because it took less than 5 minutes to complete or more than 60 minutes (1st and 99th percentile respectively). Of the remaining 4,916 cases, 55 (1.10%) were discarded because their geolocation revealed that they lied about being in Argentina. That left us with 4,861 cases (97.12% of the original 5,005 cases). Summary statistics for this final sample can be found in Table 5.

Pre-treatment variables (questions 1 to 13) that are continuous are turned into dummies (equal to 1 when it is equal or larger than the median). *Right*, *Center* and *Left* are constructed taking the value given to the performance of center-right former president Mauricio Macri minus the value given center-left former president Cristina Kirchner; from question 10c. *Raoult Bad System* captures conspiratorial beliefs by asking the respondents about their conclusions after a French physician was disciplined for promoting the use of hydroxychloroquine (reported in footnote 2). *Distrusts Government* is a dummy constructed using the first principal component of questions that asked about the performance during the pandemic of the national and local government. *Pro Ruda* aims to capture beliefs (and behaviors) about non-traditional medicine since Ruda Macho is a popular infusion in South America with alleged benefits against rheumatism and bad luck. The *Cowboy* variable indicates a respondent who doesn't want to have tests that her physician thinks she should have. It is inspired by Cutler, Skinner, Stern and Wennberg (2019) who classify physicians as "Cowboys" whenever they push for treatments that are beyond what is suggested by clinical guidelines. Similarly, the *Independence* question refers to whether the subject considers independence (versus obeyance to the rules) as an important quality in a child. *Skeptic* is constructed by taking the first principal component of *Raoult Bad System, Distrusts Government, Distrusts Scientists, Distrusts Business, Cowboy* and *Pro Ruda* and creating a dummy variable which equals one when the first principal component is larger than its median.

After the pre-treatment questions respondents were randomized into four groups.[27] Treatments consisted of an "introduction" to a question about their personal knowledge and use of NaIHS (question 14). One part, referring to the existence of NaIHS, was included in all groups:

> *We would like to ask you about nebulized ibuprofen, one of the treatments for COVID used in Argentina during the pandemic. This treatment consists of reformulating ibuprofen through a hypertonic solution and making it directly reach the lung through nebulization. Because it is a modification of standard ibuprofen its cost is very low (less than a dollar per dose). Just as with other treatments available at the start of the pandemic, it was used without a clinical trial (the scientific method through which the efficacy and security of a new medicine is established).*

Subjects in **Treatment 1 (T1-Control)** read only this part.

Treatment 2 (T2-Popular) informed respondents that NaIHS was also being widely used. Thus, in addition to the text used in T1-Control, they also read the following paragraph:

> *At the start of the pandemic, nebulized ibuprofen was available in a few private clinics but, after a network of pharmacies started to deliver it for free in several pharmacies, it also begun to be used in public hospitals. It is estimated that more than 60,000 people with COVID were treated with nebulized ibuprofen. In particular, its use was very extensive in the province of Córdoba, where around 35% of towns used it (including the biggest cities in the province, such as Córdoba capital).*

Treatment 3 (T3-Joint) added positive information regarding NaIHS' effectiveness. It added to the previous two paragraphs (i.e., to the two paragraphs in T2-Popular) a text explaining that some evidence suggested it was effective. It read:

> *From the start of the pandemic, newspapers reported that good results were being obtained, even in seriously ill patients. On August 5th, 2020, Clarin newspaper, for example, documented the treatment on two patients older than 75 years that needed a respirator due to their oxygen saturation levels: "In five days they were impeccable.*

[27] A translation of the survey can be read in Appendix B and taken (in Spanish) at the following link.

Doctors can't believe it. In one day, the saturation level climbed to 97 percent..." Later, different research projects were able to also verify improvements in larger numbers of patients, many of them in critical condition prior to receiving the treatment. Separately, a member of the network of pharmacies stated, "we do not know of a single patient that did not respond positively." In fact, of the 10 cities (over 10,000 inhabitants) of the province of Córdoba with fewest deaths per capita, 7 used nebulized ibuprofen."

Finally, we included one group that was informed of the opposition to NaIHS on the part of regulators and medical societies. **Treatment 4 (T4-Regulation)** combines the basic paragraph informing subjects of the existence of NaIHS in **T1-Control** (the control group) with the following paragraph:

A peculiarity of this treatment is the opposition of regulators and medical societies. The Administración Nacional de Medicamentos y Tecnología (ANMAT), the part of government in charge of authorizing and regulating medicines in Argentina, came out against the use of nebulized ibuprofen, even explaining that "because the product is not authorized at national level, it does not have approval for transit" between provinces. The Argentine Society of Infectious Disease (SADI) and the Argentine Society of Intensive Care (SATI) also came out against it.

Table 6 shows that pre-treatment characteristics are broadly balanced across intervention groups, suggesting a successful randomization. Six of the mean differences are statistically different from zero, which is in line with what is statistically expected at the 10% level when conducting 60 differences of means tests. In our regressions we include all pre-treatment variables as controls.

IV.b. Emprical Strategy:

We estimate the effect of our interventions by running the following regression:

$$NaIHS_i = \beta_1 + \beta_2\, T2_i + \beta_3\, T3_i \; + \beta_4\, T4_i + \delta X_i + \mu_i$$

where $T2_i$, $T3_i$, and $T4_i$ indicate the assignment of individual *i* to the respective study arms, that is, whether person *i* read the paragraph corresponding to one of the four treatments (**Control, Popular, Joint** and **Regulation**).; and μ_i is a random error term. X_i is a vector of control variables included to improve precision, as controls are not needed to address bias given the randomized design. $NaIHS_i$ is respondent's *i* answer to one of the questions capturing demand for NaIHS. We included two questions, one asking for an action in a hypothetical scenario and the second for a vote in a campaign to support the approval of NaIHS. They give rise to four measures:

1. $NaIHS\ Demand_i$ is the answer to the question: "*What is your position regarding nebulized ibuprofen as a treatment for COVID*?" The answers were recorded on a slide with 10 points and the words "I am certain I would never use it" under the number 1 and "I am certain I would use it if I had COVID" under 10. (Question 16).
2. $NaIHS\ Fan_i$ is a dummy taking the value of 1 if the score is 7 (median) or more in the previous question.
3. $NaIHS\ Yes_i$ is a dummy equal to 1 if the respondent supports a campaign for the approval of NaIHS, with the commitment on our part of writing to the government informing them of the results of the survey. (Question 17).
4. $NaIHS\ 1_i$ is a dummy equal to 1 if the respondent $NaIHS\ Yes_i = \mathbf{1}$ and scores 7 or more in the $NaIHS\ Fan_i$ variable.

We are interested in the learning effect once we control for peer effect. Thus, we first identify a "pure" learning effect by looking at the difference between the effects of T3 versus T2. This is given by the linear combination $\beta_3 - \beta_2$. That is, if T3-Joint did not include the T2-Popular paragraph, one could argue that the learning effect is bundled with a peer effect. When being informed about the effectiveness of the treatment, the reader could also infer that is being used widely. By telling readers in the third treatment arm that NaIHS was not only effective but widely used, we can then subtract the peer effect associated with T2-Popular from the effect of T3-Joint and obtain this so called "pure" learning effect. We also study β_4, the effect of information on regulatory status. We note that it was too expensive to refer to the adoption rates and performance of each subject's neighbors in the treatments, so the results are not directly comparable to the way we estimate learning or peer effects in our panel of towns.

IV.c. Results:

The raw data reveals that NaIHS is well known, with almost 36% of our sample reporting that either a family member or themselves had consumed it. A further 41% report that they know somebody that had been treated with NaIHS, for a total of 77% exposure to NaIHS. Only 6% of the sample had never heard of NaIHS.

Table 7 uses our final sample of 4,861 observations to present some basic correlations between the pre-treatment variables and our four measures of demand for NaIHS. Leaning right ideologically is positively correlated with all NaIHS outcome variables. Trust (including trust in government) have a positive association with NaIHS. Valuing independence and being classified as a Cowboy patient have a negative association with NaIHS. The opposite is true for people classified as religious or who report the consumption of traditional medicine (*Pro Ruda*). There is a negative association with NaIHS, albeit with different levels of statistical significance, of being male, old (non-linear), living in the country's capital (richest district), and having high educational attainment. Interestingly, the type of health coverage (a key, health-relevant, socio-economic trait) is uncorrelated with NaIHS. Going from being classified as left to right takes the share of respondents who score 7 or more in the NaIHS Demand question and approves the NaIHS campaign from 36.3% to 43.9%, even after controlling for beliefs that are often correlated with political identification.

Learning and Peer Effects on Preference for NaIHs

Table 8 (a) turn~~s~~ to experimental evidence. In all columns the coefficients on **T3-Joint** and **T2-Popular** go in the expected direction. The same is true for the difference (**T3-T2**) which approximates a pure learning effect because it suggests that, even after conditioning on the popularity of NaIHS (which can be called a "peer effect") subjects respond to information, "learning" about its effectiveness. To get a sense of the size, consider column (4) which has a dichotomous dependent variable. The baseline for people who were not exposed to treatment 2 nor treatment 3 is 0.364. That is, 36.4% of this group supports the NaIHS approval campaign and scores 7 or more in the NaIHS demand question. To this, we can add the 0.085 to achieve a 44.9% in the group treated with the joint treatment. Or we can add the 0.032 T2 coefficient to the same 0.364 baseline to arrive to the 39.6%

in the group treated with the popularity treatment. Moreover, the pure learning effect is significant at the 5% level or less in all specifications. The coefficient on "peer effects" is somewhat more unstable. We interpret these findings as people being influenced by their peers but mainly by the perceived effectiveness of the miracle cure. It appears that, even in the case of a non-standard medicine, people try to rationally build evidence when considering its adoption.

Table 8 (b) presents regressions of NaIHS preference on **T4-Regulation.** There is a large and statistically significant negative impact that is robust across measures of NaIHS preference.

Figure 6 (a) pulls the peer, pure learning and regulation average treatment effects together.

Heterogeneity in Learning and Conspiratorial Beliefs

We note that the treatment effects differ across groups, notably when splitting the sample by political orientation. Table 9 (a) interacts an indicator of whether a respondent is on the right with T2 and T3. The popularity treatment only affects the demand for NaIHS of left wingers. The $Right_i \times (T3_i - T2_i)$ line shows that most of the "pure" learning comes from right-wing respondents: subjects on the right increase their demand for NaIHS upon reading that it was effective (controlling for the popularity information) 7.53% points more than left wing subjects. This is driven by the fact that left wing subjects already increase their demand NaIHS upon reading that it was popular (treatment T2). 42.1% of right-wing subjects demand NaIHS in the control condition, decreasing to 40.8% with the popular treatment (T2). In contrast, 31.9% of left wingers demand NaIHS in the control condition, increasing to 38.7% after reding that it is popular (T2). After reading information that NaIHS is both popular and appears to be effective (T3), 50.3% of right-wing subjects and 40.7% of left-wing subjects demand NaIHS.

Table 9 (b) interacts political orientation with T4 and shows that, if anything, right wingers want relatively *more* NaIHS after reading that regulators and medical societies warn against its use (though this estimate is not statistically significant).

Tables 10 (a) and (b) repeats the exercise replacing *Right* with *Skeptic* (which is constructed using some of the unusual beliefs captured in our survey). It shows that those classified as *Skeptic increase* their demand for NaIHS after exposure to the regulation and this time the effect is statistically significant.[28]

Figure 6 (b) summarizes the peer, learning, and regulation effects for the *Right* and *Skeptic* groups.

We asked a question about conspiratorial beliefs regarding NaIHS, namely why was NaIHS not approved by the regulator (with 1 on a 10-point scale corresponding to "because it doesn't work" and 10 to because "it is a very cheap medicine and pharmaceutical companies have a lot of influence over doctors and regulators"). The median for the whole sample is 8, and in all arms a minimum of 25% of the sample (and a maximum of 30%) answer 10, the most conspiratorial answer. Controlling for

[28] Regressing *NaIHS Demand* on the interaction between *T4* with the variables that are used in the principal component for Skeptic yields (robust standard errors in brackets): *Raoult Bad System* 0.282 (0.218), *Distrusts Government* 0.590***(0.210), *Distrusts Scientists* 0.314 (0.211), *Distrusts Business* 0.068 (0.211), *Cowboy* 0.258 (0.211) and *Pro Ruda* -0.085 (0.224). Table A6 shows that the *Skeptic x T4* interaction remains negative and significant after controlling for the *Right x T4* interaction.

conspiratorial beliefs captured by *Raoult Bad System*, there is a strong positive correlation with *Religious* and the use of traditional medicine (*Pro Ruda*) and a negative correlation with *Cowboy, Independence* and *Distrusts Scientists.* It is interesting that a counterpart of enthusiastic doctors adopting a clinically unproven drug (albeit in desperate circumstances) is a belief in regulatory capture by special interests amongst the general public. As expected, there is not a strong impact of the treatments on the answers. Only T4 causes somewhat lower scores on average (in the subsample of subjects classified as Skeptic the effect of T4 is precisely estimated at zero).

V. Conclusions

This study documents the widespread use of a "miracle cure" against COVID-19 accompanied by expert and regulatory opposition and unusual beliefs by consumers. It also documents how a part of this demand was consistent with a rational attempt to learn about its effectiveness.

The case we study is the diffusion of nebulized ibuprofen (NaIHS) as a treatment during the pandemic in Argentina. By the end of the second wave, it had been administered to approximately 100,000 patients spread throughout the country despite a complete lack of clinical evidence and many public warnings against its use by the federal regulator and professional societies. Such widespread diffusion together with uncertain status, as well as the fact that it was pushed by thousands of doctors without a direct financial incentive, suggests it is appropriate to separate NaIHS from cases of "snake oil," which is the name typically given to fraudulent drugs. We describe the basic data for this "miracle drug" and test if its diffusion involved patterns that can be described as rational learning, even when it happened well outside a standard scientific setting. We also study the role of ideologies and beliefs in affecting NaIHS adoption and the role of regulation.

Our paper exploits two original sources of data. The first involves all NaIHS deliveries across 491 towns in the province of Córdoba during the pandemic. The second is a survey of 4,861 individuals living in Argentina at the end of the pandemic. The simple correlations are interesting. For example, lower educational attainment is correlated with demand for this miracle drug in both data sets. The same is true about geographic remoteness and being governed by (or identification with, in the case of the survey) the center-right political party that is in the opposition during this period. The survey provides other interesting correlations between beliefs and the demand for a miracle drug.

Our main result is that there is a process that can be described as learning in both data sets, in the sense that good news about its effectiveness increases the adoption of NaIHS, even after controlling for its popularity amongst peers. The two data sets use different identification strategies. Using our panel of towns, we exploit the timing of COVID related deaths in towns as opportunities for information transmission about the effectiveness of each town's strategy to fight the pandemic. Our survey allows us to recover causal effects through random assignment of information treatments.

We also study heterogeneous effects. In the panel, learning is broadly similar across towns of different political orientation. In the survey, in contrast, center right subjects react to positive information on the effectiveness of NaIHS by demanding more, even after controlling for its popularity. Left wingers only react to information suggesting NaIHS is popular. Information on the negative position of the regulator and medical societies has a significant, negative effect on demand for NaIHS only in the center-left leaning group. Finally, we build a variable called "skeptic" using unusual beliefs (for example, those that exhibit low trust or those that accept a conspiratorial account of the suspension of hydroxychloroquine as a cure for COVID in France). Those classified as skeptic, *significantly increase* their demand for NaIHS when primed with information on the regulator's resistance to NaIHS.

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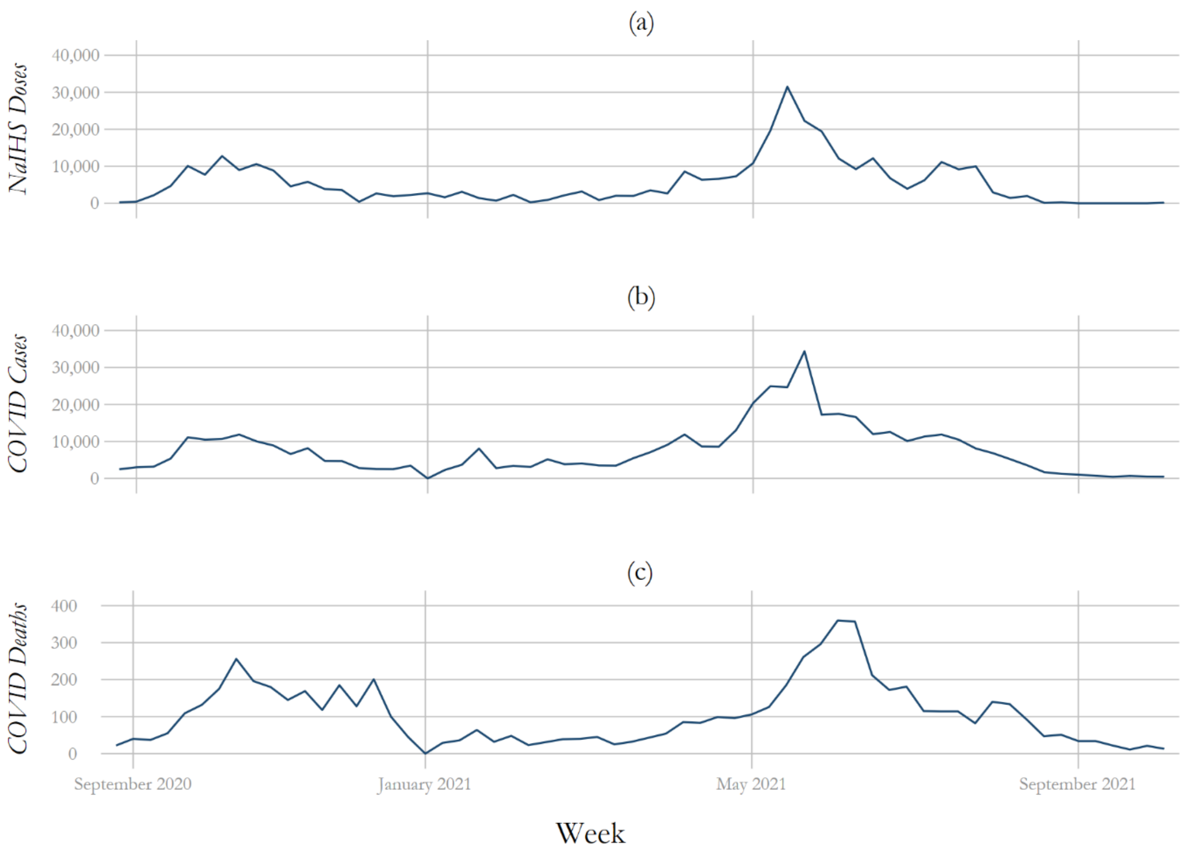
Figure 1. Delivery of NaIHS through "Helmet"

Source: "Coronavirus en Argentina: investigadores cordobeses prueban con éxito un tratamiento con ibuprofeno." *Clarin*, May 7, 2020.

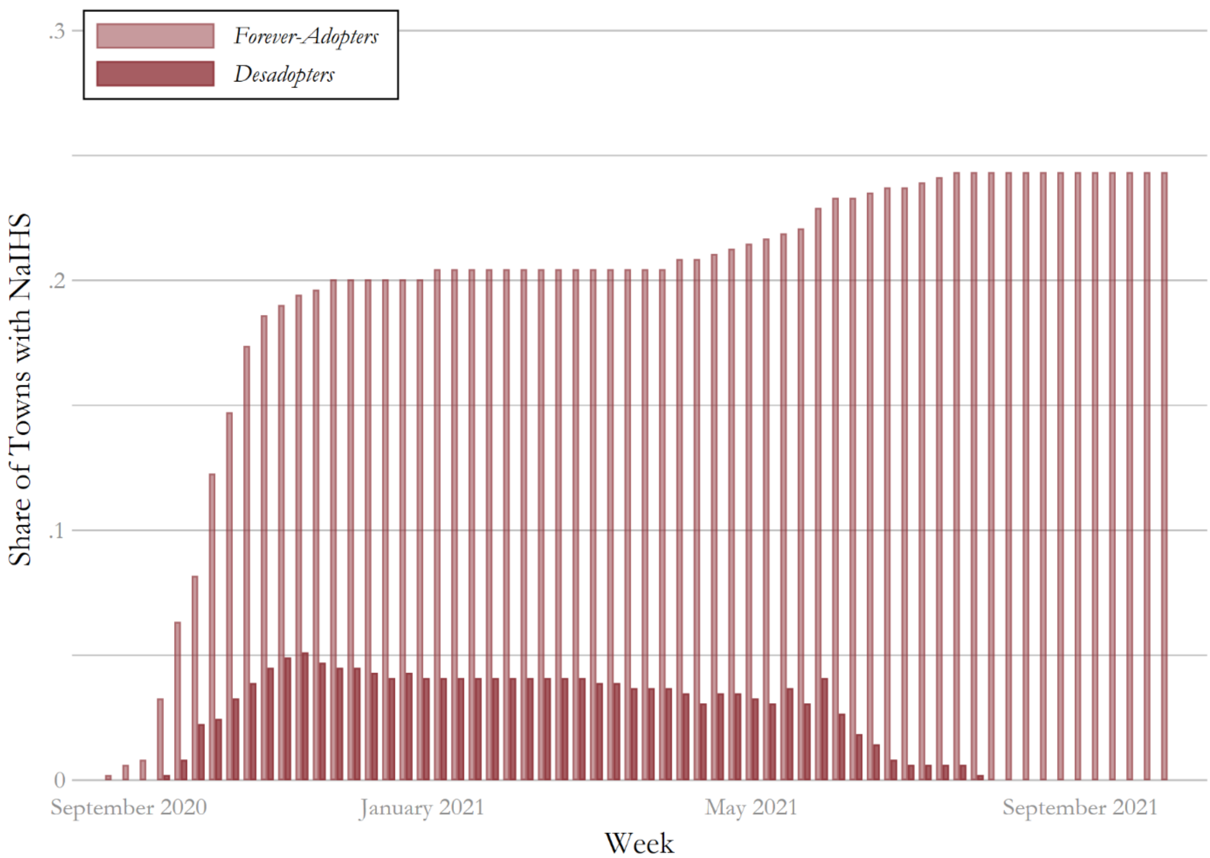
Figure 2. NaIHS Diffusion in the Province of Córdoba

NaIHS Doses, COVID Cases and COVID Deaths



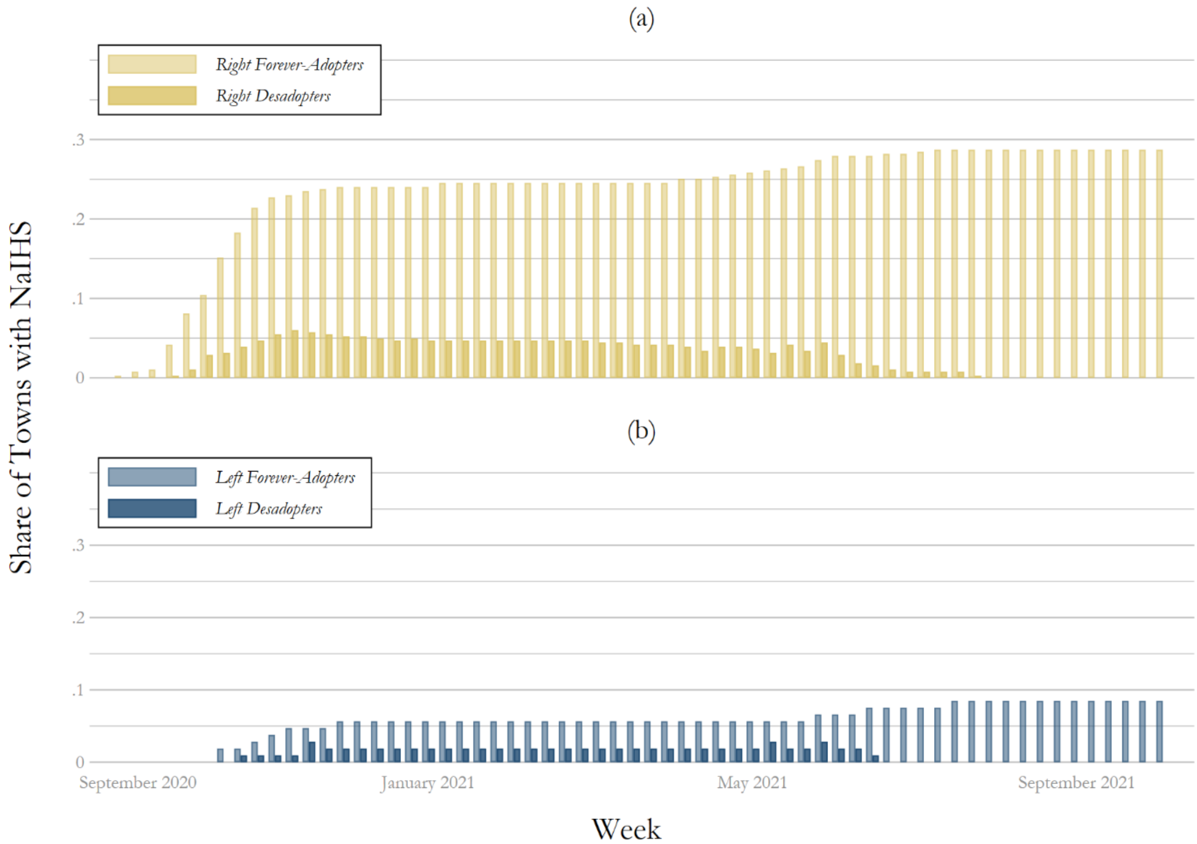
Notes: Sample consists of 491 towns in the province of Córdoba over 62 weeks. Official data on COVID-19 cases and deaths at the town level was obtained from the Center of Emergency Operations (C.O.E.). Data on deliveries was provided by *Química Luar*.

Figure 3. NaIHS Diffusion in the Province of Córdoba



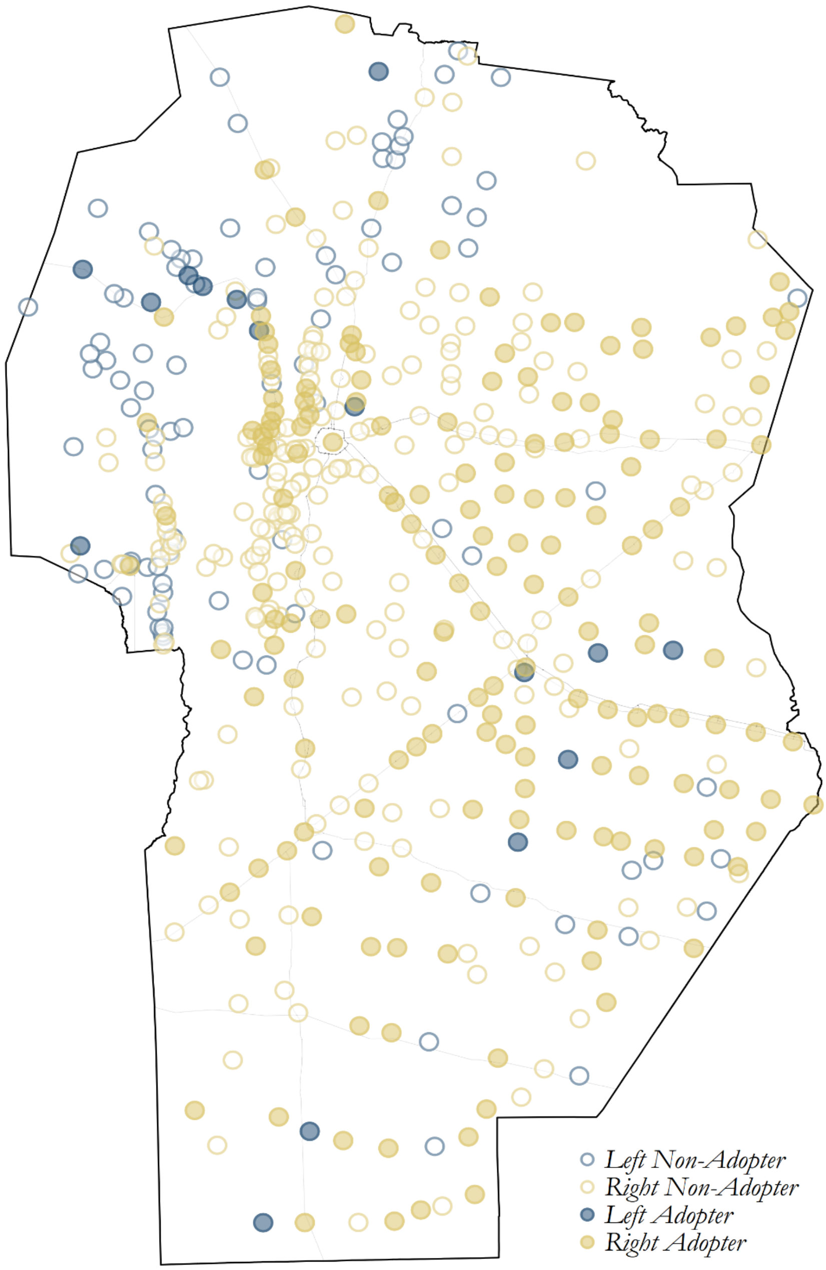
Notes: Sample consists of 491 towns in the province of Córdoba over 62 weeks. Towns are all initially classified as N*on-Adopters*. It is classified as an *Adopter* when it orders NaIHS for the first time. Within *Adopters,* if the town keeps demanding NaIHS, it is classified as *Forever-Adopter*. But if the town will not order NaIHS again despite accumulating "enough" COVID deaths, they are classified as a *Desadopter* (the threshold is calculated as the median deaths per capita of towns that ordered for a second time). Note that "stacking" *Desadopters* and *Forever-Adopters* bars would give you an *Adopters* bar (omitted).

Figure 4. NaIHS Diffusion in the province of Córdoba, by Town's Political Orientation



Note: Sample consists of 491 towns in the province of Córdoba over 62 weeks. All towns are initially classified as N*on-Adopters*, switching to *Adopter* when it orders NaIHS for the first time. *Adopter* towns are further classified as *Forever-Adopter* if they continue demanding NaIHS. But they are classified as a *Desadopter* if at some point in the future they accumulate "enough" COVID deaths without ordering NaIHS again (the threshold is calculated as the median deaths per capita of towns that ordered for a second time). *Right* is a dummy variable taking the value of 1 for the town if Macri got a higher percentage of votes than Fernández in 2019 presidential election. There are 384 *Right* towns and 107 *Left* towns. The share is calculated within towns of the same political alignment. Note that "stacking" *Desadopters* and *Forever-Adopters* bars would give you an *Adopters* bar (omitted).

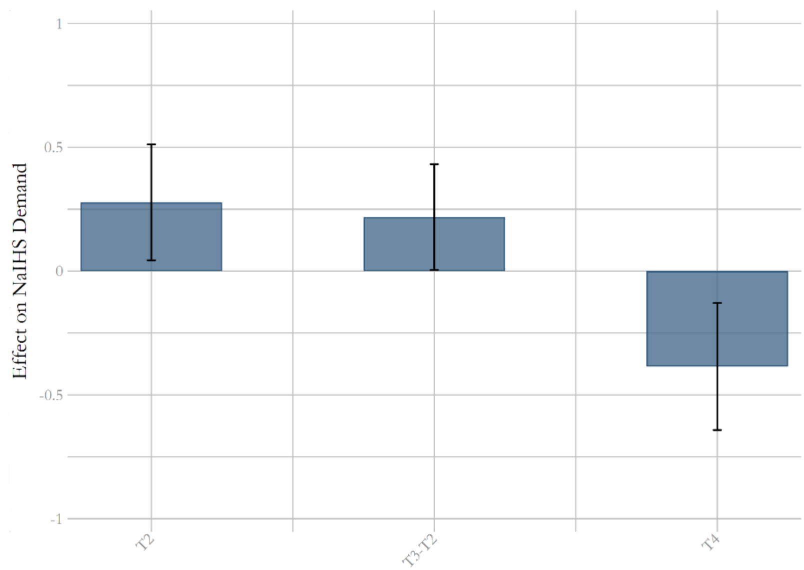
Figure 5. NaIHS Geographical Diffusion in the Province of Córdoba



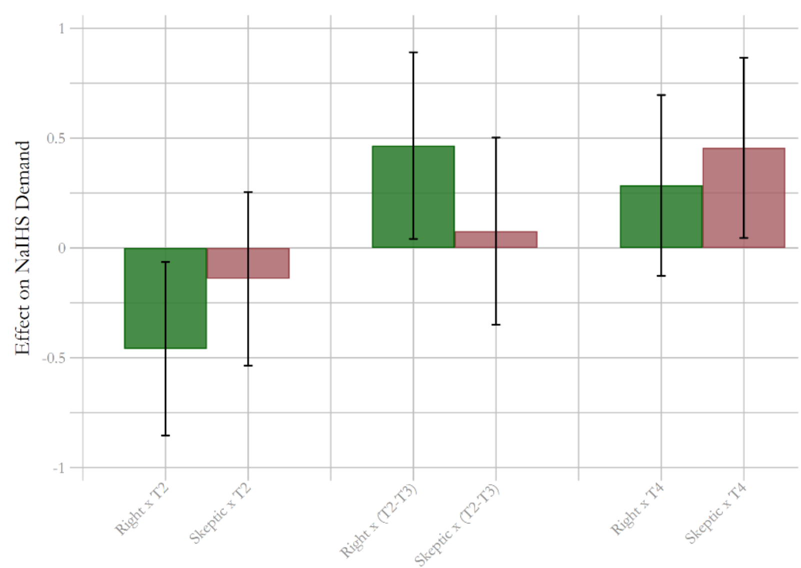
Note: Sample consists of 491 towns in the province of Córdoba over 62 weeks. Gray lines are the main routes of the province. Towns are all initially classified as *Non-Adopters*. A town is classified as an *Adopter* when it orders NaIHS for the first time. *Right* is a dummy variable taking the value of 1 for the town if Macri got a higher percentage of votes than Fernández in 2019 presidential election. There are 384 *Right* towns and 107 *Left* towns. Share is within towns of the same political alignment.

Figures 7. NaIHS Demand for a Survey of Individuals.

(a) Peer, Pure Learning and Regulation Effects



(b) Peer, Pure Learning and Regulation Effects Interaction with Right and Skeptic



Notes: Final sample of 4,861 individuals consists of people who spent more than 5 and less than 60 minutes answering the survey and who we did not geocode to be outside of Argentina. Coefficients from Table 8, 9 and 10 are presented in bars, 95% confidence intervals from robust standard errors in lines. *NaIHS Demand* is the answer to the question "What is your position regarding nebulized ibuprofen as a treatment for COVID?". *T2* refers to Popular treatment, *T3* to Joint treatment and *T3-T2* represents a "pure" learning effect. *T4* refers to Regulation treatment. *Right* is a dummy variable taking the value of 1 when the respondent ranks Macri higher than Kirchner. *Skeptic* is a dummy variable taking the value of 1 when the first principal component of *Raoult Bad System*, *Distrusts Government*, *Distrusts Scientists*, *Distrusts Business*, *Cowboy* and *Pro Ruda* is larger than its median. Regressions control for all variables included in Table 7.

Table 1. Summary Statistics for a Panel of Towns in the Province of Córdoba

	Observations	Mean	SD	Min	Max
Adoption Status					
Non-Adopters	307	0.63	0.48	0.00	1.00
Adopter	184	0.37	0.48	0.00	1.00
Forever-Adopters	120	0.24	0.43	0.00	1.00
Desadopters	64	0.13	0.34	0.00	1.00
Early-Adopters	74	0.15	0.36	0.00	1.00
Late-Adopters	110	0.22	0.42	0.00	1.00
Determinants					
Right	384	0.78	0.41	0.00	1.00
Left	107	0.22	0.41	0.00	1.00
Distance to Córdoba	-	131.25	84.53	0.00	381.50
Distance to Hospital	-	29.76	19.67	0.43	113.06
Computers	-	33.68	14.18	1.19	94.77
Mobile Phones	-	85.19	10.51	2.22	100.00
College	-	6.10	4.54	0.00	32.40
Commune	337	0.69	0.46	0.00	1.00
Municipality	111	0.23	0.42	0.00	1.00
City	43	0.09	0.28	0.00	1.00
Population	-	6373	60183	20.00	1317298
Cumulative Cases	-	978	9440	0.00	206366
Cumulative Deaths	-	13.40	130.37	0.00	2844.00

Notes: Sample consists of 491 towns in the province of Córdoba. Towns are all initially classified as N*on-Adopters*. A town is classified as an *Adopter* when it orders NaIHS for the first time. *Adopter* towns that keep demanding NaIHS are classified as *Forever-Adopter*. *Adopter* towns that, at some point in the future, did not order NaIHS again despite accumulating "enough" COVID deaths are classified as *Desadopter* (the threshold is calculated as the median deaths per capita of towns that ordered for a second time). *Adopters* can also be classified into *Early-Adopters* if they ordered for the first time during the first seven weeks of our sample. Otherwise, they are classified as *Late-Adopters*.

Table 2. Cross-Sectional Correlations for a Panel of Towns

	(1) Adopter	(2) Forever-Adopter	(3) Early-Adopter
Right	0.080*	0.082	0.209*
	(0.043)	(0.147)	(0.119)
Distance to Córdoba (100 kms.)	0.093***	0.020	0.188***
	(0.026)	(0.047)	(0.043)
Distance to Hospital (100 kms.)	-0.062	-0.073	0.048
	(0.099)	(0.213)	(0.196)
Computers	0.014***	0.005	0.000
	(0.002)	(0.007)	(0.007)
Mobile Phones	-0.005***	-0.002	0.008*
	(0.002)	(0.004)	(0.005)
College	-0.021***	-0.034*	0.017
	(0.006)	(0.018)	(0.018)
Municipality	0.293***	0.092	0.023
	(0.058)	(0.092)	(0.079)
City	0.509***	0.269**	0.191
	(0.067)	(0.120)	(0.117)
Population (10,000 habitants)	0.015	0.018	-0.026
	(0.050)	(0.080)	(0.100)
Cumulative Cases	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Cumulative Deaths	0.000	0.004	0.000
	(0.002)	(0.003)	(0.004)
Observations	491	184	184
Moran's Test	0.014	-0.007	0.004
p-value	0.000	0.447	0.138

Notes: Sample consists of 491 towns in the province of Córdoba. Towns are all initially classified as N*on-Adopters*. A town is classified as an *Adopter* when it orders NaIHS for the first time. *Adopter* towns that keep demanding NaIHS are classified as *Forever-Adopter*. *Adopter* towns that, at some point in the future, did not order NaIHS again despite accumulating "enough" COVID deaths are classified as *Desadopter* (the threshold is calculated as the median deaths per capita of towns that ordered for a second time). *Adopters* can also be classified into *Early-Adopters* if they ordered for the first time during the first seven weeks of our sample. Otherwise, they are classified as *Late-Adopters*. Column (1) compares *Adopters* vs *Non-Adopters*, Column (2) *Forever-Adopters vs Desadopters* and Column (3) *Early-Adopters* vs *Late-Adopters*.

Table 3. Adoption of NaIHS for a Panel of Towns in the Province of Córdoba

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$	(4) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.972***	0.969***	0.860***	0.788***
	(0.002)	(0.003)	(0.010)	(0.011)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.026	0.026	0.032	0.043**
	(0.018)	(0.019)	(0.020)	(0.021)
$\overline{NaIHS}_{n(i),t-1}$	0.009	-0.005	0.010	0.008
	(0.008)	(0.011)	(0.013)	(0.018)
Observations	29950	29950	29950	29950
Town Specific Trend	No	No	No	Yes
Department FE	No	Yes	No	No
Town FE	No	No	Yes	Yes

Notes: Sample consists of 491 towns in the province of Córdoba over 62 weeks. $NaIHS_{i,t}$ is a time-varying dummy variable that takes the value of 1 when the town orders NaIHS for the first time and (i) does not turn off to zero if the town ordered NaIHS again or did not accumulate enough COVID deaths to justify ordering again (ii) turns off to zero if the town did not order NaIHS again despite having enough COVID deaths to justify ordering again. $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ are distance-from-i-weighted average COVID deaths of towns that adopted NaIHS at period t-1, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ are distance-from-i-weighted average COVID deaths of towns that did not adopt NaIHS at period t-1 and $\overline{NaIHS}_{n(i),t-1}$ are distance-from-i-weighted average number of adopters at period t-1. There are 26 departments in the province of Córdoba. All the controls in Table 2 included here as well as period fixed effects.

Table 4. Adoption of NaIHS for a Panel of Towns and Interaction with Political Orientation

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$	(4) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.972***	0.969***	0.860***	0.787***
	(0.002)	(0.003)	(0.010)	(0.011)
$(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1)$	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$Right_i$	0.012**	0.012**	-0.014*	-0.053***
	(0.006)	(0.006)	(0.007)	(0.014)
$Right_i \times (\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1)$	0.001	0.001	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0)$	0.048***	0.048***	0.052***	0.057***
	(0.018)	(0.019)	(0.019)	(0.021)
$Right_i \times (\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0)$	-0.053**	-0.052**	-0.045	-0.028
	(0.025)	(0.025)	(0.029)	(0.030)
$\overline{NaIHS}_{n(i),t-1}$	0.014	-0.000	0.004	-0.008
	(0.009)	(0.012)	(0.014)	(0.019)
$Right_i \times \overline{NaIHS}_{n(i),t-1}$	-0.012*	-0.010	0.008	0.026**
	(0.007)	(0.007)	(0.008)	(0.013)
Observations	29950	29950	29950	29950
Town Specific Trend	No	No	No	Yes
Department FE	No	Yes	No	No
Town FE	No	No	Yes	Yes

Notes: Sample consists of 491 towns in the province of Córdoba over 62 weeks. $NaIHS_{i,t}$ is a time-varying dummy variable that takes the value of 1 when the town orders NaIHS for the first time and (i) does not turn off to zero if the town ordered NaIHS again or did not accumulate enough COVID deaths to justify ordering again (ii) turns off to zero if the town did not order NaIHS again despite having enough COVID deaths to justify ordering again. $(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1)$ are distance-from-i-weighted average COVID deaths of towns that adopted NaIHS at period t-1, $(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0)$ are distance-from-i-weighted average COVID deaths of towns that did not adopt NaIHS at period t-1 and $\overline{NaIHS}_{n(i),t-1}$ are distance-from-i-weighted average number of adopters at period t-1. There are 26 departments in the province of Córdoba. All the controls in Table 2 included here as well as period fixed effects. $Right_i$ is a dummy variable taking the value of 1 for the town if Macri got a higher percentage of votes than Fernández in 2019 presidential election.

Table 5. Summary Statistics for a Survey of Individuals

	N	Mean	SD	Min	Max
Outcomes					
NaIHS Demand	-	6.52	3.00	0	10
NaIHS Fan	2637	0.54	0.50	0	1
NaIHS Yes	2407	0.50	0.50	0	1
NaIHS 1	1927	0.40	0.49	0	1
Determinants		0.44	0.50	0	1
Right	2157	0.44	0.50	0	1
Left	1638	0.34	0.47	0	1
Raoult Bad System	2979	0.61	0.49	0	1
Distrusts Government	2428	0.50	0.50	0	1
Distrusts Scientists	2597	0.53	0.50	0	1
Distrusts Business	2630	0.54	0.50	0	1
Pro Ruda	3125	0.64	0.48	0	1
Cowboy	2526	0.52	0.50	0	1
Independence	2732	0.56	0.50	0	1
Messi Better	2108	0.43	0.50	0	1
Maradona Better	1349	0.28	0.45	0	1
Religious	2484	0.51	0.50	0	1
Higher Education	2441	0.50	0.50	0	1
Private Health Coverage	1164	0.24	0.43	0	1
Public Health Coverage	1630	0.34	0.47	0	1
Male	1699	0.35	0.48	0	1
Age	-	51.93	14.29	18	93
Buenos Aires	1554	0.32	0.47	0	1
CABA	1024	0.21	0.41	0	1
Córdoba	1200	0.25	0.43	0	1

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina.

Table 6. Balance Table for a Survey of Individuals

	(1) Mean T1	(2) Mean T2	(3) Mean T3	(4) Mean T4	(5) T2 vs T1	(6) T3 vs T1	(7) T4 vs T1
Right	0.451	0.441	0.435	0.451	-0.010	-0.015	0.000
	(0.498)	(0.497)	(0.496)	(0.498)	(0.020)	(0.020)	(0.021)
Left	0.333	0.333	0.348	0.333	-0.000	0.015	-0.000
	(0.472)	(0.471)	(0.476)	(0.472)	(0.019)	(0.019)	(0.020)
Raoult Bad System	0.627	0.612	0.602	0.612	-0.014	-0.025	-0.015
	(0.484)	(0.487)	(0.490)	(0.488)	(0.020)	(0.020)	(0.021)
Distrusts Government	0.509	0.497	0.501	0.491	-0.013	-0.008	-0.019
	(0.500)	(0.500)	(0.500)	(0.500)	(0.020)	(0.020)	(0.021)
Distrusts Scientists	0.552	0.506	0.553	0.527	-0.046**	0.001	-0.026
	(0.498)	(0.500)	(0.497)	(0.500)	(0.020)	(0.020)	(0.021)
Distrusts Business	0.555	0.520	0.552	0.539	-0.035*	-0.003	-0.016
	(0.497)	(0.500)	(0.497)	(0.499)	(0.020)	(0.020)	(0.021)
Pro Ruda	0.637	0.649	0.638	0.648	0.012	0.002	0.011
	(0.481)	(0.478)	(0.481)	(0.478)	(0.019)	(0.019)	(0.021)
Cowboy	0.528	0.509	0.534	0.506	-0.019	0.006	-0.022
	(0.499)	(0.500)	(0.499)	(0.500)	(0.020)	(0.020)	(0.021)
Independence	0.561	0.555	0.551	0.586	-0.006	-0.010	0.025
	(0.496)	(0.497)	(0.498)	(0.493)	(0.020)	(0.020)	(0.021)
Messi Better	0.441	0.445	0.431	0.415	0.005	-0.010	-0.026
	(0.497)	(0.497)	(0.495)	(0.493)	(0.020)	(0.020)	(0.021)
Maradona Better	0.277	0.258	0.300	0.273	-0.019	0.023	-0.004
	(0.448)	(0.438)	(0.459)	(0.446)	(0.018)	(0.018)	(0.019)
Religious	0.520	0.517	0.516	0.488	-0.003	-0.004	-0.032
	(0.500)	(0.500)	(0.500)	(0.500)	(0.020)	(0.020)	(0.021)
Higher Education	0.482	0.503	0.500	0.526	0.021	0.019	0.044**
	(0.500)	(0.500)	(0.500)	(0.500)	(0.020)	(0.020)	(0.021)
Private Health Coverage	0.243	0.253	0.229	0.232	0.010	-0.014	-0.011
	(0.429)	(0.435)	(0.420)	(0.423)	(0.017)	(0.017)	(0.018)
Public Health Coverage	0.346	0.322	0.349	0.324	-0.023	0.004	-0.022
	(0.476)	(0.467)	(0.477)	(0.468)	(0.019)	(0.019)	(0.020)
Male	0.348	0.376	0.343	0.325	0.028	-0.005	-0.023
	(0.477)	(0.485)	(0.475)	(0.469)	(0.019)	(0.019)	(0.020)
Age	53.327	51.633	51.031	51.974	-1.694***	-2.296***	-1.352**
	(14.265)	(14.442)	(14.148)	(14.200)	(0.581)	(0.574)	(0.610)
Buenos Aires	0.322	0.316	0.321	0.320	-0.006	-0.001	-0.003
	(0.468)	(0.465)	(0.467)	(0.467)	(0.019)	(0.019)	(0.020)
CABA	0.213	0.199	0.223	0.207	-0.013	0.010	-0.006
	(0.409)	(0.400)	(0.416)	(0.405)	(0.016)	(0.017)	(0.017)
Córdoba	0.259	0.256	0.240	0.231	-0.003	-0.019	-0.028
	(0.438)	(0.436)	(0.427)	(0.422)	(0.018)	(0.017)	(0.018)
Observations	1,123	1,329	1,355	1,054	2,452	2,478	2,177

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. Means and mean differences are presented in first rows, robust standard errors in the second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 7. Correlations for a Survey of Individuals

	(1) NaIHS Demand	(2) NaIHS Fan	(3) NaIHS Yes	(4) Ibu 1
Right	0.467***	0.070***	0.086***	0.078***
	(0.117)	(0.019)	(0.020)	(0.019)
Left	-0.113	-0.009	0.001	-0.003
	(0.125)	(0.020)	(0.020)	(0.020)
Raoult Bad System	0.074	-0.018	0.077***	0.043***
	(0.091)	(0.015)	(0.015)	(0.015)
Distrusts Government	-0.209**	-0.042**	-0.026	-0.037**
	(0.102)	(0.017)	(0.017)	(0.017)
Distrusts Scientists	-0.444***	-0.072***	-0.049***	-0.074***
	(0.093)	(0.015)	(0.015)	(0.015)
Distrusts Business	-0.304***	-0.057***	-0.056***	-0.054***
	(0.090)	(0.015)	(0.015)	(0.015)
Pro Ruda	0.424***	0.064***	0.106***	0.075***
	(0.090)	(0.015)	(0.015)	(0.014)
Cowboy	-0.426***	-0.073***	-0.029**	-0.064***
	(0.088)	(0.014)	(0.014)	(0.014)
Independence	-0.167*	-0.038***	-0.010	-0.026*
	(0.088)	(0.014)	(0.015)	(0.014)
Messi Better	0.188*	0.032*	0.054***	0.045***
	(0.104)	(0.017)	(0.017)	(0.017)
Maradona Better	0.160	0.029	0.033*	0.023
	(0.115)	(0.019)	(0.019)	(0.018)
Religious	0.177**	0.058***	0.018	0.036**
	(0.087)	(0.015)	(0.015)	(0.014)
Higher Education	-0.349***	-0.064***	-0.017	-0.036**
	(0.094)	(0.016)	(0.016)	(0.016)
Private Health Coverage	0.065	0.004	-0.019	-0.014
	(0.111)	(0.019)	(0.019)	(0.018)
Public Health Coverage	0.052	0.001	-0.002	-0.005
	(0.109)	(0.017)	(0.018)	(0.017)
Male	-0.155*	-0.010	0.043***	0.019
	(0.092)	(0.015)	(0.015)	(0.015)
Age	0.058***	0.006*	0.010***	0.009***
	(0.019)	(0.003)	(0.003)	(0.003)
Age Sq. (100 years)	-0.054***	-0.004	-0.010***	-0.008***
	(0.018)	(0.003)	(0.003)	(0.003)
Buenos Aires	-0.076	-0.020	-0.021	-0.042**
	(0.125)	(0.021)	(0.021)	(0.021)
CABA	-0.429***	-0.094***	-0.077***	-0.096***
	(0.132)	(0.022)	(0.023)	(0.022)
Córdoba	0.341***	0.054**	0.005	0.005
	(0.126)	(0.021)	(0.021)	(0.021)
Observations	4,861	4,861	4,861	4,861
R-squared	0.050	0.062	0.042	0.047

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. OLS coefficients are presented in first rows, robust standard errors in second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Tables 8. NaIHS Demand for a Survey of Individuals

(a) Popular and Joint Treatments

	(1) $NaIHS$ Demand$_i$	(2) $NaIHS$ Fan$_i$	(3) $NaIHS$ Yes$_i$	(4) $NaIHS$ 1$_i$
$T3_i$	0.496***	0.073***	0.071***	0.085***
	(0.118)	(0.019)	(0.020)	(0.019)
$T2_i$	0.278**	0.020	0.034*	0.032*
	(0.119)	(0.020)	(0.020)	(0.020)
$T3_i - T2_i$	0.218	0.053	0.037	0.052
p-val	0.045	0.004	0.050	0.005
Baseline	6.308	0.517	0.466	0.364
N	4861	4861	4861	4861

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. OLS coefficients are presented in first rows, robust standard errors in second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. $NaIHS\ Demand_i$ is a 1 ("I am certain I would never use it") to 10 ("I am certain I would use it if I had COVID") answer to the question "What is your position regarding nebulized ibuprofen as a treatment for COVID?". $NaIHS\ Fan_i$ is a dummy taking the value of 1 if the respondent scores 7 or more in the previous $NaIHS\ Demand$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $NaIHS\ 1_i$ is a dummy variable taking the value of 1 if the $NaIHS\ Fan_i$ and the $NaIHS\ Yes_i$ dummy variables take the value of 1. T2 refers to Popular treatment, T3 to Joint treatment and T3-T2 combines them linearly by subtraction representing a "pure" learning effect. p-val refers to the associated p-value of that linear combination. Baseline (T2 = 0) refers to predicted NaIHS Demand with all variables at means but T2, which is at 0. Baseline refers to the value the outcome variable takes when all variables are at means but T2 and T3, which are at 0. Controls include T4 and all variables included in Table 7.

(b) Regulation Treatment

	(1) $NaIHS$ Demand$_i$	(2) $NaIHS$ Fan$_i$	(3) $NaIHS$ Yes$_i$	(4) $NaIHS$ 1$_i$
$T4_i$	-0.385***	-0.067***	-0.036*	-0.040**
	(0.131)	(0.021)	(0.021)	(0.020)
Baseline	6.606	0.557	0.503	0.405
N	4861	4861	4861	4861

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. OLS coefficients are presented in first rows, robust standard errors in second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. $NaIHS\ Demand_i$ is a 1 ("I am certain I would never use it") to 10 ("I am certain I would use it if I had COVID") answer to the question "What is your position regarding nebulized ibuprofen as a treatment for COVID?". $NaIHS\ Fan_i$ is a dummy taking the value of 1 if the respondent scores 7 or more in the previous $NaIHS\ Demand$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $NaIHS\ 1_i$ is a dummy variable taking the value of 1 if the $NaIHS\ Fan_i$ and the $NaIHS\ Yes_i$ dummy variables take the value of 1. T4 refers to Regulation treatment. Baseline refers to the value the outcome variable takes when all variables are at means but T4, which is at 0. Controls include T2, T3 and all variables included in Table 7.

Table 9. NaIHS Demand for a Survey of Individuals and Interactions with Political Ideology

(a) Popular and Joint Treatments Interaction with Right

	(1) $NaIHS$ Demand$_i$	(2) $NaIHS$ Fan$_i$	(3) $NaIHS$ Yes$_i$	(4) $NaIHS$ 1_i
$Right_i$	0.596***	0.084***	0.097***	0.102***
	(0.153)	(0.025)	(0.025)	(0.024)
$T3_i$	0.495***	0.063**	0.074***	0.088***
	(0.154)	(0.024)	(0.025)	(0.024)
$Right_i \times T3_i$	0.006	0.024	-0.006	-0.006
	(0.200)	(0.033)	(0.034)	(0.033)
$T2_i$	0.481***	0.051**	0.049*	0.068***
	(0.155)	(0.025)	(0.025)	(0.024)
$Right_i \times T2_i$	-0.459**	-0.070**	-0.032	-0.081**
	(0.202)	(0.034)	(0.034)	(0.034)
$Right_i \times (T3_i - T2_i)$	0.466	0.094	0.027	0.075
p-val	0.032	0.012	0.480	0.046
Baseline (T2 = 0)	6.043	0.479	0.423	0.319
N	4861	4861	4861	4861

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. OLS coefficients are presented in first rows, robust standard errors in second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. $NaIHS\ Demand_i$ is a 1 ("I am certain I would never use it") to 10 ("I am certain I would use it if I had COVID") answer to the question "What is your position regarding nebulized ibuprofen as a treatment for COVID?". $NaIHS\ Fan_i$ is a dummy taking the value of 1 if the respondent scores 7 or more in the previous $NaIHS\ Demand$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $NaIHS\ 1_i$ is a dummy variable taking the value of 1 if the $NaIHS\ Fan_i$ and the $NaIHS\ Yes_i$ dummy variables take the value of 1. T2 refers to Popular treatment, T3 to Joint treatment and T3-T2 combines them linearly by subtraction representing a "pure" learning effect. p-val refers to the associated p-value of that linear combination. Right is a dummy variable taking the value of 1 when the respondent ranks from 1("Very bad president") to 5 ("Very good president") Macri higher than Kirchner. Baseline refers to the value the outcome variable takes when all variables are at means but T2, T3 and Right, which are at 0. Controls include T4 and all variables included in Table 7.

(b) Regulation Treatment Interaction with Right

	(1) $NaIHS$ Demand$_i$	(2) $NaIHS$ Fan$_i$	(3) $NaIHS$ Yes$_i$	(4) $NaIHS$ 1_i
$Right_i$	0.408***	0.058***	0.075***	0.063***
	(0.124)	(0.020)	(0.021)	(0.020)
$T4_i$	-0.514***	-0.094***	-0.060**	-0.070***
	(0.163)	(0.026)	(0.026)	(0.024)
$Right_i \times T4_i$	0.285	0.059*	0.052	0.068**
	(0.210)	(0.034)	(0.034)	(0.033)
Baseline	6.425	0.531	0.470	0.377
N	4861	4861	4861	4861

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. Coefficients are presented in first rows, robust standard errors in second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. $NaIHS\ Demand_i$ is a 1 ("I am certain I would never use it") to 10 ("I am certain I would use it if I had COVID") answer to the question "What is your position regarding nebulized ibuprofen as a treatment for COVID?". $NaIHS\ Fan_i$ is a dummy taking the value of 1 if the respondent scores 7 or more in the previous $NaIHS\ Demand$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $NaIHS\ 1_i$ is a dummy variable taking the value of 1 if the $NaIHS\ Fan_i$ and the $NaIHS\ Yes_i$ dummy variables take the value of 1. T4 refers to Regulation treatment. Right is a dummy variable taking the value of 1 when the respondent ranks from 1("Very bad president") to 5 ("Very good president") Macri higher than Kirchner. Baseline refers to the value the outcome variable takes when all variables are at means but T4 and Right, which are at 0. Controls include T2, T3 and all variables included in Table 7.

Table 10. NaIHS Demand for a Survey of Individuals and Interactions with Beliefs.

(a) Popular and Joint Treatments Interaction with Skeptic

	(1) $NaIHS$ Demand$_i$	(2) $NaIHS$ Fan$_i$	(3) $NaIHS$ Yes$_i$	(4) $NaIHS$ 1_i
$Skeptic_i$	0.156	0.058*	0.044	0.054*
	(0.195)	(0.032)	(0.032)	(0.031)
$T3_i$	0.532***	0.096***	0.076***	0.105***
	(0.160)	(0.025)	(0.026)	(0.026)
$Skeptic_i \times T3_i$	-0.064	-0.043	-0.006	-0.037
	(0.201)	(0.033)	(0.034)	(0.033)
$T2_i$	0.349**	0.051**	0.047*	0.054**
	(0.161)	(0.026)	(0.026)	(0.026)
$Skeptic_i \times T2_i$	-0.141	-0.062*	-0.024	-0.041
	(0.202)	(0.034)	(0.034)	(0.033)
$Skeptic_i \times (T3_i - T2_i)$	0.076	0.019	0.018	0.004
p-val	0.726	0.616	0.638	0.910
Baseline	6.229	0.487	0.444	0.337
N	4861	4861	4861	4861

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. OLS coefficients are presented in first rows, robust standard errors in second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. $NaIHS\ Demand_i$ is a 1 ("I am certain I would never use it") to 10 ("I am certain I would use it if I had COVID") answer to the question "What is your position regarding nebulized ibuprofen as a treatment for COVID?". $NaIHS\ Fan_i$ is a dummy taking the value of 1 if the respondent scores 7 or more in the previous $NaIHS\ Demand$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $NaIHS\ 1_i$ is a dummy variable taking the value of 1 if the $NaIHS\ Fan_i$ and the $NaIHS\ Yes_i$ dummy variables take the value of 1. T2 refers to Popular treatment, T3 to Joint treatment and T3-T2 combines them linearly by subtraction representing a "pure" learning effect. p-val refers to the associated p-value of that linear combination. Skeptic is a dummy variable taking the value of 1 when the first principal component of *Raoult Bad System, Distrusts Government, Distrusts Scientists, Distrusts Business, Cowboy* and *Pro Ruda* is larger than its median. Baseline refers to the value the outcome variable takes when all variables are at means but T2, T3 and Right, which are at 0. Controls include T4 and all variables included in Table 7.

(b) Regulation Treatment Interaction with Skeptic

	(1) $NaIHS$ Demand$_i$	(2) $NaIHS$ Fan$_i$	(3) $NaIHS$ Yes$_i$	(4) $NaIHS$ 1$_i$
$Skeptic_i$	0.004	0.007	0.031	0.016
	(0.170)	(0.028)	(0.028)	(0.028)
$T4_i$	-0.607***	-0.116***	-0.045*	-0.076***
	(0.169)	(0.027)	(0.027)	(0.026)
$Skeptic_i \times T4_i$	0.456**	0.100***	0.019	0.074**
	(0.209)	(0.034)	(0.034)	(0.032)
Baseline	6.604	0.553	0.488	0.397
N	4861	4861	4861	4861

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. OLS coefficients are presented in first rows, robust standard errors in second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. $NaIHS\ Demand_i$ is a 1 ("I am certain I would never use it") to 10 ("I am certain I would use it if I had COVID") answer to the question "What is your position regarding nebulized ibuprofen as a treatment for COVID?". $NaIHS\ Fan_i$ is a dummy taking the value of 1 if the respondent scores 7 or more in the previous $NaIHS\ Demand$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $NaIHS\ 1_i$ is a dummy variable taking the value of 1 if the $NaIHS\ Fan_i$ and the $NaIHS\ Yes_i$ dummy variables take the value of 1. T4 refers to Regulation treatment. Skeptic is a dummy variable taking the value of 1 when the first principal component of *Raoult Bad System, Distrusts Government, Distrusts Scientists, Distrusts Business, Cowboy* and *Pro Ruda* is larger than 0.55. Baseline refers to the value the outcome variable takes when all variables are at means but T4 and Skeptic, which are at 0. Controls include T2, T3 and all variables included in Table 7.

Appendix A: Panel's Additional Tables Appendix

Appendix A1: Robustness to trimming time-series dimension.

In this robustness check we do not trim the 19 weeks beyond the first week without deaths in our panel, so our sample is increased to 81 weeks. Table A1 replicates Table 3 under this new sample. Results are practically identical.

Table A1. Adoption of NaIHS for a Panel of Towns – Non-Trimmed Time Series Dimension

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$	(4) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.979***	0.976***	0.883***	0.800***
	(0.002)	(0.002)	(0.009)	(0.010)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.026	0.027	0.031*	0.038**
	(0.016)	(0.017)	(0.017)	(0.019)
$\overline{NaIHS}_{n(i),t-1}$	0.009	-0.005	0.009	0.007
	(0.007)	(0.010)	(0.013)	(0.017)
Observations	39279	39279	39279	39279
Town Specific Trend	No	No	No	Yes
Department FE	No	Yes	No	No
Town FE	No	No	Yes	Yes

Notes: Non-trimmed time series dimension sample of 491 Córdoba province's towns during 81 weeks. $NaIHS_{i,t}$ is a time-varying dummy variable that takes the value of 1 when the town orders NaIHS for the first time and (i) does not turn off to zero if the town ordered NaIHS again or did not accumulate enough COVID deaths to justify ordering again (ii) turns off to zero if the town did not order NaIHS again despite having enough COVID deaths to justify ordering again. $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ are distance-from-i-weighted average COVID deaths of towns that adopted NaIHS at period t-1, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ are distance-from-i-weighted average COVID deaths of towns that did not adopt NaIHS at period t-1 and $\overline{NaIHS}_{n(i),t-1}$ are distance-from-i-weighted average number of adopters at period t-1. There are 26 departments in the province of Córdoba, which are the geographical unit most similar to US counties. Controls include all the time-invariant variables in Table 2 and i's cumulative COVID deaths and cases as time-variant variables. Period FE also included in all columns.

Appendix A2: Robustness to discrete outcome variable

In this robustness check, instead of $NaIHS_{i,t}$ being the discrete outcome variable described above, $NaIHS_{i,t}$ is a continuous outcome variable that represents, at each period, the cumulative doses ordered by each town. Table A2 replicates Table 3 using this new dependent variable. Note that $\overline{NaIHS}_{n(i),t-1}$ also needed to change. Not only coefficients which were significant remained so at the 1% level but also now all coefficients associated with $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ are significant at the 1%. Now 12 out of 16 coefficients are significant at the 1% level. Coefficients also remain stable across specifications. Coefficients got larger since the new dependent variable now may take larger values too.

Table A2. Adoption of NaIHS for a Panel of Towns - Continuous Outcome Variable

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$	(4) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	1.019*** (0.001)	1.015*** (0.002)	0.988*** (0.002)	0.944*** (0.020)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-3.264*** (1.239)	-2.888*** (0.953)	-2.172*** (0.783)	-3.178*** (1.002)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	64.262*** (23.420)	71.123*** (24.470)	58.550*** (19.436)	73.844*** (27.569)
$\overline{NaIHS}_{n(i),t-1}$	0.000** (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Observations	29950	29950	29950	29950
Town Specific Trend	No	No	No	Yes
Department FE	No	Yes	No	No
Town FE	No	No	Yes	Yes

Notes: Final sample of 491 Córdoba province's towns during 62 weeks. $NaIHS_{i,t}$ is a continuous variable that represents, at each period, the cumulative doses ordered by each town. . $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ are distance-from-i-weighted average COVID deaths of towns that adopted NaIHS at period t-1, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ are distance-from-i-weighted average COVID deaths of towns that did not adopt NaIHS at period t-1 and $\overline{NaIHS}_{n(i),t-1}$ are distance-from-i-weighted average cumulative doses at period t-1. There are 26 departments in the province of Córdoba, which are the geographical unit most similar to US counties. Controls include all the time-invariant variables in Table 2 and i's cumulative COVID deaths and cases as time-variant variables. Period FE also included in all columns.

Appendix A3: Robustness to Buera et al. (2011) model

A possible concern is that NaIHS adoption cannot be always considered a town policy (in the way financial liberalization can be always considered a country policy in Buera et al., 2011). The larger the town, the less concentrated the public health decisions are. In order to address this concern, we make two routes. First, we drop (in a very specific way described below) big towns from our sample. Second, we drop (in a specific fashion described below) towns where we are not certain that the deliveries were made to an administrative or health related institution of the town.

(a) Robustness to big towns

We proceed to drop the 25 towns in the upper quintile of population (above 16,238 habitants). The specific way in which we do this is that we allow small towns to learn from these big towns and have them in their networks, but big cities do not enter our estimation. That is, the calculations that small towns make for $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ and $\overline{NaIHS}_{n(i),t-1}$ include big towns, but the regression we run does not include big cities as i. Table A3a replicates Table 3 with this new data. Results are practically identical.

(b) Robustness to non-town-specific institutions

In the NaIHS deliveries data there is some information that we ignored until now: within each town we know to which institutions the delivery was made. Specifically, we classify these institutions as town council (35.41% of the deliveries made within the Córdoba province), hospitals (15.54%), clinics (37.24), private (11.81%, includes physicians, pharmacists, nursing homes, etc.). We then drop the 19 towns that do not have at least one delivery explicitly made to the town council. The specific way we drop these towns is the same as the one described above. Table 3 is replicated under this new sample in Table A3b. Results are practically identical.

Table A3

(a) Adoption of NaIHS for a Panel of Towns – Small Towns

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$	(4) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.972*** (0.003)	0.969*** (0.003)	0.859*** (0.011)	0.787*** (0.012)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.004*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.027 (0.019)	0.025 (0.019)	0.031 (0.021)	0.041* (0.022)
$\overline{NaIHS}_{n(i),t-1}$	0.017** (0.008)	0.002 (0.011)	0.012 (0.013)	0.003 (0.019)
Observations	28426	28426	28426	28426
Town Specific Trend	No	No	No	Yes
Department FE	No	Yes	No	No
Town FE	No	No	Yes	Yes

Notes: Alternative small towns sample of 466 Córdoba province's towns during 62 weeks. $NaIHS_{i,t}$ is a time-varying dummy variable that takes the value of 1 when the town orders NaIHS for the first time and (i) does not turn off to zero if the town ordered NaIHS again or did not accumulate enough COVID deaths to justify ordering again (ii) turns off to zero if the town did not order NaIHS again despite having enough COVID deaths to justify ordering again. $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ are distance-from-i-weighted average COVID deaths of towns that adopted NaIHS at period t-1, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ are distance-from-i-weighted average COVID deaths of towns that did not adopt NaIHS at period t-1 and $\overline{NaIHS}_{n(i),t-1}$ are distance-from-i-weighted average number of adopters at period t-1. There are 26 departments in the province of Córdoba, which are the geographical unit most similar to US counties. Controls include all the time-invariant variables in Table 2 and i's cumulative COVID deaths and cases as time-variant variables. Period FE also included in all columns.

(b) Adoption of NaIHS for a Panel of Towns – Town-Specific Deliveries

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$	(4) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.973***	0.970***	0.855***	0.789***
	(0.002)	(0.003)	(0.011)	(0.011)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.017	0.014	0.022	0.033
	(0.017)	(0.018)	(0.019)	(0.021)
$\overline{NaIHS}_{n(i),t-1}$	0.011	-0.002	0.010	0.006
	(0.008)	(0.011)	(0.013)	(0.019)
Observations	28791	28791	28791	28791
Town Specific Trend	No	No	No	Yes
Department FE	No	Yes	No	No
Town FE	No	No	Yes	Yes

Notes: Alternative town-specific deliveries sample of 472 Córdoba province's towns during 62 weeks. $NaIHS_{i,t}$ is a time-varying dummy variable that takes the value of 1 when the town orders NaIHS for the first time and (i) does not turn off to zero if the town ordered NaIHS again or did not accumulate enough COVID deaths to justify ordering again (ii) turns off to zero if the town did not order NaIHS again despite having enough COVID deaths to justify ordering again. $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ are distance-from-i-weighted average COVID deaths of towns that adopted NaIHS at period t-1, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ are distance-from-i-weighted average COVID deaths of towns that did not adopt NaIHS at period t-1 and $\overline{NaIHS}_{n(i),t-1}$ are distance-from-i-weighted average number of adopters at period t-1. There are 26 departments in the province of Córdoba, which are the geographical unit most similar to US counties. Controls include all the time-invariant variables in Table 2 and i's cumulative COVID deaths and cases as time-variant variables. Period FE also included in all columns.

Appendix A4: Robustness to 7 days period

This robustness check collapses the daily data to 5 days periods, so our sample is increased to 86 periods. Table A4 replicates Table 3 under this new sample. Results are practically identical.

Table A4. Adoption of NaIHS for a Panel of Towns – 5 days period

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$	(4) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.980***	0.978***	0.898***	0.843***
	(0.002)	(0.002)	(0.007)	(0.008)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.017	0.015	0.021	0.025
	(0.015)	(0.016)	(0.015)	(0.015)
$\overline{NaIHS}_{n(i),t-1}$	0.004	-0.008	-0.000	0.012
	(0.007)	(0.009)	(0.011)	(0.013)
Observations	41735	41735	41735	41735
Town Specific Trend	No	No	No	Yes
Department FE	No	Yes	No	No
Town FE	No	No	Yes	Yes

Notes: Alternative 5 days periods sample of 491 Córdoba province's towns during 86 weeks. $NaIHS_{i,t}$ is a time-varying dummy variable that takes the value of 1 when the town orders NaIHS for the first time and (i) does not turn off to zero if the town ordered NaIHS again or did not accumulate enough COVID deaths to justify ordering again (ii) turns off to zero if the town did not order NaIHS again despite having enough COVID deaths to justify ordering again. $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ are distance-from-i-weighted average COVID deaths of towns that adopted NaIHS at period t-1, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ are distance-from-i-weighted average COVID deaths of towns that did not adopt NaIHS at period t-1 and $\overline{NaIHS}_{n(i),t-1}$ are distance-from-i-weighted average number of adopters at period t-1. There are 26 departments in the province of Córdoba, which are the geographical unit most similar to US counties. Controls include all the time-invariant variables in Table 2 and i's cumulative COVID deaths and cases as time-variant variables. Period FE also included in all columns.

Appendix A5: Robustness to neighbors' definition

A potential concern is that the exponentially decaying weights in our definition of neighbors capture is a mechanical approach to capturing the way that towns relate nearby towns. One alternative is to define neighbors through regional football leagues (football is by far the most popular sport in Argentina). The least important professional league (but still with professional players) is organized at the regional level. Every province has between 1 and 61 regional leagues, with each league hosting between 10 and 40 teams. These teams belong to the towns and usually carry the towns' names. There is a long tradition, with some of teams founded in the late 19th century. The leagues are played all year long and teams must visit each other, with the fans travelling to support them.

Córdoba has 18 regional leagues that host a total of 367 teams (with a median of 20 teams per league) spread across 189 towns. For towns that do not have a team of their own, we impute them with the team of the nearest town. That is, we are assuming that towns that don't have a team of their own support the team of the nearest town. With this new definition of neighbors, we reconstruct the $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ and $\overline{NaIHS}_{n(i),t-1}$ variables with the exponential decaying distance weights but now we restrict the neighbors to be in the same regional league than the town's i team. That is, in the estimation included in the main body of this paper, town i received information from all the towns of the province, with an exponentially decaying distance weight. Now, town i receives information only from towns that have teams that play in the same league, with an exponentially decaying distance weight. Table 3 is replicated under this new definition in Table A5.

Table A5. Adoption of NaIHS for a Panel of Towns – Soccer League Neighbors

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$	(4) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.9736***	0.9704***	0.8360***	0.7101***
	(0.0024)	(0.0026)	(0.0149)	(0.0170)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.0004***	-0.0004*	-0.0004***	-0.0004*
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	-0.0006	-0.0005	0.0043	0.0097
	(0.0071)	(0.0073)	(0.0085)	(0.0088)
$\overline{NaIHS}_{n(i),t-1}$	0.0084***	0.0004	0.0143*	0.0172
	(0.0026)	(0.0034)	(0.0086)	(0.0121)
Observations	29950	29950	29950	29950
Town Specific Trend	No	No	No	Yes
Department FE	No	Yes	No	No
Town FE	No	No	Yes	Yes

Notes: Final sample of 491 Córdoba province's towns during 62 weeks. $NaIHS_{i,t}$ is a time-varying dummy variable that takes the value of 1 when the town orders NaIHS for the first time and (i) does not turn off to zero if the town ordered NaIHS again or did not accumulate enough COVID deaths to justify ordering again (ii) turns off to zero if the town did not order NaIHS again despite having enough COVID deaths to justify ordering again. $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ are distance-from-i-weighted average COVID deaths of towns that adopted NaIHS at period t-1, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ are distance-from-i-weighted average COVID deaths of towns that did not adopt NaIHS at period t-1 and $\overline{NaIHS}_{n(i),t-1}$ are distance-from-i-weighted average number of adopters at period t-1. These weighted averages are calculated for towns within the same soccer league. There are 18 soccer leagues in the province of Córdoba. There are 26 departments in the province of Córdoba, which are the geographical unit most similar to US counties. Controls include all the time-invariant variables in Table 2 and i's cumulative COVID deaths and cases as time-variant variables. Period FE also included in all columns.

Table A6. Regulation Treatment Interaction with Skeptic and Right

	(1) $NaIHS$ Demand$_i$	(2) $NaIHS$ Fan$_i$	(3) $NaIHS$ Yes$_i$	(4) $NaIHS$ 1_i
$Skeptic_i$	0.012	0.009	0.033	0.018
	(0.170)	(0.028)	(0.028)	(0.028)
$T4_i$	-0.660***	-0.126***	-0.061**	-0.091***
	(0.182)	(0.029)	(0.029)	(0.028)
$Skeptic_i \times T4_i$	0.409*	0.090***	0.005	0.060*
	(0.219)	(0.035)	(0.035)	(0.034)
$Right_i$	0.432***	0.063***	0.075***	0.067***
	(0.125)	(0.020)	(0.021)	(0.020)
$Right_i \times T4_i$	0.167	0.033	0.050	0.051
	(0.220)	(0.035)	(0.035)	(0.034)
Baseline	6.409	0.525	0.453	0.366
N	4861	4861	4861	4861

Notes: Final sample of 4,861 individuals consists of people who spent more than 5 and less than 60 minutes answering the survey and who we did not geocode to be outside of Argentina. OLS coefficients are presented in first rows, robust standard errors in second. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. $NaIHS\ Demand_i$ is a 1 ("I am certain I would never use it") to 10 ("I am certain I would use it if I had COVID") answer to the question "What is your position regarding nebulized ibuprofen as a treatment for COVID?". $NaIHS\ Fan_i$ is a dummy taking the value of 1 if the respondent scores 7 or more in the previous $NaIHS\ Demand$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $NaIHS\ 1_i$ is a dummy variable taking the value of 1 if the $NaIHS\ Fan_i$ and the $NaIHS\ Yes_i$ dummy variables take the value of 1. *T4* refers to Regulation treatment. Skeptic is a dummy variable taking the value of 1 when the first principal component of *Raoult Bad System*, *Distrusts Government*, *Distrusts Scientists*, *Distrusts Business, Cowboy* and *Pro Ruda* is larger than its median. *Right* is a dummy variable taking the value of 1 when the respondent ranks from 1 ("Very bad president") to 5 ("Very good president") Macri higher than Kirchner. Baseline refers to the value the outcome variable takes when all variables are at means but *T4*, *Skeptic* and *Right* which are at 0. Controls include T4 and all variables included in Table 7.

Appendix B: Survey Instrument (Translated from Spanish)

1. In which of the following jurisdictions do you live?

   □ Autonomous City of Buenos Aires
   □ Province of Córdoba
   □ Province of Neuquén
   □ Other

2. Please indicate if you are…
   □ Female
   □ Male
   □ Other

3. How old are you? ....

4. What is the highest educational level you achieved?

   □ Primary not completed
   □ Primary completed
   □ Secondary not completed
   □ Secondary completed
   □ Tertiary/university not completed
   □ Tertiary completed
   □ University completed

5. Name up to three cities or towns with which you usually have contact (for example, because you visited them or received news from them)

   - ………………………………………..
   - ………………………………………..
   - ………………………………………..

6. What type of medical coverage do you have?

   □ Prepaid (OSDE, Medicus, OMINT, etc.)
   □ Social Insurance (OSFE, Health Prevention, Hierarchical, etc.)
   □ I do not have coverage (I go to a public hospital if I want to be treated by a doctor)

7. you consider yourself a religious person?

   Move the circle left and right to find the value that best fits your answer.

   I am not a believer < □ □ □ □ □ □ □ □ □ □ > I am a believer and I practice

8. We want to ask your opinion about the government's management during the COVID pandemic that began in 2020.
   a. How good do you think the national government's handling of the pandemic was?

Very bad < □ □ □ □ □ □ □ □ □ □ > Very good

b. And the management of the government of the town where you live?

Very bad < □ □ □ □ □ □ □ □ □ □ > Very good

9. These two groups receive praise for their work, but also criticism when they prioritize their economic interest. How much trust do you have in each of these groups?

a. Business-owners

No confidence < □ □ □ □ □ □ □ □ □ □ > A lot of confidence

b. Scientists

No confidence < □ □ □ □ □ □ □ □ □ □ > A lot of confidence

10. We want to record your opinion on three very different topics (parenting, soccer and politics). In your opinion:

a. What quality do you consider most important for a child to learn at home?

Learn to understand and obey the rules of society	< □ □ □ >	To be independent to make his choices

b. Who is a better soccer player?

□ Messi
□ Maradona
□ They are equal

c. How good presidents were Cristina Kirchner and Mauricio Macri?

Cristina Kirchner
□ Very bad president
□ Bad
□ Fair
□ Good
□ Very good president

Mauricio Macri
□ Very bad president
□ Bad
□ Fair
□ Good
□ Very good president

11. The following is an attention check: please select among the geometric figures listed below, the first one that appears in the list:
□ Triangle
□ Rhombus
□ Round
□ Square

The following questions are about medicine in general:

12. Suppose that just before visiting your doctor for your annual checkup, you notice mild chest pain when walking up the stairs. Suppose your doctor explains to you that he doesn't think it's serious but that you should still have some tests (blood tests, x-rays, etc.) and see a specialist.

I would FOR SURE follow the doctor's recommendation (I would have tests and visit a specialist)	< □ □ □ >	For sure I would NOT follow the doctor's recommendation (I would not have tests nor visit a specialist)

13. Ruda (also called Ruda Macho) is a plant that is popularly used against bad luck, but it is also used in traditional medicine despite the lack of scientific evidence in its favor. Its applications range from the treatment of mild ailments (such as stomach pain) to severe conditions (such as kidney problems). Did you know any of these uses of Ruda? Do you think it could have a positive effect?

□ I have consumed it on some occasion
□ Although I don't consume it, I knew that it has recommendable properties.
□ I know it, but I would never consume it
□ I didn't know Ruda

14. At the beginning of the pandemic, the prestigious French doctor Didier Raoult proposed modifying chloroquine to treat COVID patients. It is a medication originally prescribed against malaria and is very cheap because it is a generic (it costs less than a dollar per dose).

The first results were very satisfactory, which is why its use became widespread (one of the first to use it was the president of the United States, Donald Trump). However, shortly after, this medication was questioned by regulators and a panel of experts from the World Health Organization (WHO). Dr. Raoult was subjected to an investigation. His main defense was that pharmaceutical companies attacked him to promote another drug, Remdesivir, on which there were no conclusive studies either but it is a better deal for them since it has a high cost ($390 per dose). What do you think about the situation?

It reflects the malfunctions of the system since it prevents the use of a promising drug	< □ □ □ >	It reflects the good functioning of the system since it prevents the use of a drug that can be harmful for health

[Survey instrument continues to question 15 which involves our 4 treatments.]

Treatment 1

15. We would like to ask you about nebulized ibuprofen, one of the treatments for COVID used in Argentina during the pandemic. This treatment consists of reformulating ibuprofen through a hypertonic solution and making it directly reach the lung through nebulization. Because it is a modification of standard ibuprofen its cost is very low (less than a dollar per dose). Just as with other treatments available at the start of the pandemic, it was used without a clinical trial (the scientific method through which the efficacy and security of a new medicine is established).

Have you heard of this treatment?

□ I know it because I (or a family member) used it as a treatment for COVID
□ I know people who used it
□ Through the media or social networks
□ I didn't know it

Treatment 2

15. We want to ask you about nebulizable ibuprofen, one of the treatments for COVID used in Argentina during the pandemic. This treatment consists of reformulating ibuprofen using a hypertonic solution and delivering it directly to the lungs through nebulization. As it is an alteration of traditional ibuprofen, its cost is very low (less than a dollar per dose). Like other treatments available at the beginning of the pandemic, nebulizable ibuprofen was used without a clinical trial (the scientific method by which the safety and effectiveness of a new medication is tested).
At the start of the pandemic, nebulized ibuprofen was available in a few private clinics but, after a network of pharmacies started to deliver it for free in several pharmacies, it also begun to be used in public hospitals. It is estimated that more than 60,000 people with COVID were treated with nebulized ibuprofen. In particular, its use was very extensive in the province of Córdoba, where around 35% of towns used it (including the biggest cities in the province, such as Córdoba capital).

Have you heard of this treatment?

□ I know it because I (or a family member) used it as a treatment for COVID
□ I know people who used it
□ Through the media or social networks
□ I didn't know it

Treatment 3

15. We want to ask you about nebulizable ibuprofen, one of the treatments for COVID used in Argentina during the pandemic. This treatment consists of reformulating ibuprofen using a hypertonic solution and delivering it directly to the lungs through nebulization. As it is an alteration of traditional ibuprofen, its cost is very low (less than a dollar per dose). Like other treatments available at the beginning of the pandemic, nebulizable ibuprofen was used without a clinical trial (the scientific method by which the safety and effectiveness of a new medication is tested).
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From the beginning of the pandemic, newspapers reported that good results were being obtained, even in seriously ill patients. On August 5th, 2020, Clarin newspaper, for example, documented the treatment on two patients older than 75 years that needed a respirator due to their oxygen saturation levels: "In five days they were impeccable. Doctors can't believe it. In one day, the saturation level climbed to 97 percent..." Later, different research projects were able to also verify improvements in larger numbers of patients, many of them in critical condition prior to receiving the treatment. Separately, a member of the network of pharmacies stated, "we do not know of a single patient that did not respond positively." In fact, of the 10 cities (over 10,000 inhabitants) of the province of Córdoba with fewest deaths per capita, 7 used nebulized ibuprofen.

Have you heard of this treatment?

□ I know it because I (or a family member) used it as a treatment for COVID
□ I know people who used it
□ Through the media or social networks
□ I didn't know it

Treatment 4

15. We want to ask you about nebulizable ibuprofen, one of the treatments for COVID used in Argentina during the pandemic. This treatment consists of reformulating ibuprofen using a hypertonic solution and delivering it directly to the lungs through nebulization. As it is an alteration of traditional ibuprofen, its cost is very low. Like other treatments available at the beginning of the pandemic, nebulizable ibuprofen was used without a clinical trial (the scientific method by which the safety and effectiveness of a new medication is tested).
A peculiarity of this treatment is the opposition on the part of regulators and medical societies. The Administración Nacional de Medicamentos y Tecnología (ANMAT), the part of government in charge of authorizing and regulating medicines in Argentina, came out against the use of nebulized ibuprofen, even explaining that "because the product is not authorized at national level, it does not have approval for transit" between provinces. The Argentine Society of Infectious Disease (SADI) and the Argentine Society of Intensive Care (SATI) also came out against it.

Have you heard of this treatment?

□ I know it because I (or a family member) used it as a treatment for COVID
□ I know people who use it
□ Through the media or social networks
□ I didn't know it

[Survey instrument continues for all 4 treatments with question 16]

16. What is your position on nebulized ibuprofen as a treatment for COVID?

For sure I would NEVER use it < □ □ □ □ □ □ □ □ □ □ > For sure I would use it if I had COVID

17. Some people are campaigning to ask the government to approve the use of nebulizable ibuprofen. Other people are on the opposite pole and are trying to get its use banned. For our part, we plan to write to the government telling them the result of this survey. What campaign would you support?

    □ I vote to support the approval campaign
    □ I vote to support the ban campaign
    □ I do not want to support any campaign

18. In these two questions we ask you to speculate about the future :

    a. How widespread will the use of nebulizable ibuprofen have been at the end of the pandemic?

For me it will have been used in FEW locations	< □ □ □ >	For me it will have been used in MANY locations

    b. When the corresponding clinical trials are completed, what will they reveal about its effectiveness?

For me it will have been proven to be useless to treat persons with COVID	< □ □ □ □ >	For me it will have been proven to be very useful to treat persons with COVID

19. Why do you think that nebulizable ibuprofen was not officially recognized as a valid treatment against COVID by the authorities?

Because it doesn't work	< □ □ □ □ >	Because it is a very cheap medicine and pharmaceutical companies have a lot of influence over doctors and regulators

To finish, we want to ask you a few last questions on different topics:

20. Another treatment that was used in Argentina as a treatment against COVID is plasma. At first it was highly recommended and a national campaign was launched for recovered COVID patients to donate plasma. But this was discontinued when some scientific studies showed that it was not as effective as believed. What is your opinion on this?

Since scientific evidence does not justify its use, it is best to suspend the campaign	< □ □ □ >	Scientific evidence is never conclusive, so I support the campaign so that doctors who wish to do so can use it on their patients

21. Which COVID vaccine did you get first?

□ China vaccine (Sinopharm, Sinovac)
□ US/UK vaccine (Pfizer, J&J, Moderna, AstraZeneca)
□ Russia vaccine (Sputnik)
□ I did not receive any COVID vaccine

22. During the 2001 crisis, banks were the focus of much criticism. One of the main criticisms is that they use inside information to benefit shareholders before the public can withdraw their savings. Do you share this criticism? Here are three opinions, which one is closest to your opinion?

    □ In crises, banks and their owners lose a lot
    □ In crises, banks and their owners manage not to lose
    □ In crises, banks and their owners never lose because they violate the law

23. Which of these candidates would you vote for in the next presidential election:

    □ Mauricio Macri (Cambiemos)
    □ Horacio Rodriguéz Larreta (Cambiemos)
    □ Sergio Massa (Frente de Todos)
    □ Cristina Kirchner (Frente de Todos)
    □ I'm not sure yet

24. The Argentine government spends a significant sum of money on social assistance and there are different positions on the matter. Which opinion is closest to yours?
    □ It should be reduced a lot and soon
    □ It should be reduced but only when the economic situation improves a little (that is, when inflation drops and the economy grows more)
    □ It should be maintained since it is related to structural poverty
    □ It should be increased since it is an important help for people who have no other option

25. Complaints frequently appear about abuses by beneficiaries (such as not putting effort into looking for work, etc.). More serious allegations include violations, such as lying on documents to receive multiple plans or engaging in identity fraud (for example, assuming the identity of a deceased person). What do you think should be done when the most serious cases are detected?
    □ Impose severe fines (equivalent to the refund of all plans granted under false pretenses)
    □ Withdraw all plans and not allow you to receive new plans for a long period of time (not before five years)
    □ Leave you the corresponding plan (take out the others).
    □ Gradually remove plans that do not correspond to you to give you time to adjust your expenses

[Survey instrument finished]