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

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ABSTRACT

We study the diffusion of a clinically unproven treatment for COVID-19 in Argentina. As the pandemic spread, nebulized ibuprofen reached thousands of patients, even some seriously ill, despite warnings by the regulator and medical societies. We use daily data on drug deliveries for all towns in one of the largest provinces to study diffusion patterns and find a role for learning. An experimental survey is also consistent with learning. A key dimension affecting diffusion is ideology: towns and subjects classified as “right-wing” are more likely to adopt and to learn.

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I. Introduction

In an influential paper, Griliches documented the existence of an "S-curve" in the diffusion of hybrid corn in the US in the 1940's, spurring a vast literature on technology adoption (Griliches, 1957). One strand of this research has long been of interest to academics studying economic growth as small differences in the diffusion of better technologies can help explain why some countries are so much richer than others (Parente & Prescott, 1994). A second strand focused on the adoption of health-related technologies, where a lot of the effort went into connecting early adoption of effective technologies to large gains in health outcomes (Skinner & Staiger, 2007, 2015). A little appreciated finding in this research is that they also document fast adoption of some less effective technologies. These two dimensions -namely that some units are more likely than others to adopt new technologies and that there is sometimes also fast adoption of less efficient technologies- became particularly relevant during the pandemic when heterogeneity in political beliefs seemed to play a key role in health-related decisions, as illustrated by Donald Trump and Jair Bolsonaro's early endorsement of hydroxicloroquine.[1]

In this paper we extend research on diffusion to consider the role of learning and political beliefs in the spread of a potentially inferior drug, in a high-stake setting and in the presence of explicit warnings of experts and regulators. Our focus is the case of nebulized ibuprofen (or NaIHS), a drug that spread wildly throughout Argentina as a "miracle cure" for COVID-19. Typically, attempts to cure people involve clinically proven drugs and treatments. At the other extreme is the case of "snake oil", the treatment of patients with unregulated products because unscientific claims are made by "quack doctors", often for money. An intermediate case involves drugs that are clinically unproven and that are explicitly rejected by the regulator and other experts but that are enthusiastically endorsed as "miraculous" by some health professionals who may have minimal or no financial interest in them (so

[1] On March 19th, 2020 the US President 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 it Emergency Use status. 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". Brazilian mayors seeking reelection followed and distributed Covid kits including hydroxychloroquine (see "Once upon a time in the chloroquine country", Agência Pública, October 13, 2020). On June 15th the FDA revoked the Emergency Use Authorization.

outright fraud is not involved).[2] This appears to be the case of NaIHS, a variant of standard ibuprofen that can be directly delivered in large quantities to the lungs using easily available inhalation devices.

Originally designed to treat cystic fibrosis, researchers conjectured that it might be useful as a treatment for patients with COVID during the initial phase of the pandemic (see García, et al., 2020).[3] At the time, the World Health Organization had recommended against taking standard ibuprofen to treat COVID patients, but the province of Córdoba authorized the nebulized version under a novel and unusual regulatory category: "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. *ANMAT* followed up with public announcements explaining that the agency had not received requests to initiate the approval process, stressing that circulation of NaIHS across provinces was prohibited by law. Eight other provinces eventually issued similar "extended compassionate use" authorizations, although use of NaIHS frequently took place outside this quasi-legal framework. For example, NaIHS was used in these 8 provinces before they had issued "extended compassionate use" authorizations, and in 10 provinces that never had one. Besides "industrial" NaIHS, a network of compounding pharmacies produced their own variety, which was distributed in 20 provinces. We document that, between August 2020 and August 2022, at least 99,453 COVID patients were treated with one of the two versions (industrial or compounded) of nebulized ibuprofen.

We compile two original data sets. The first combines data on NaIHS deliveries to each town in the second largest province of Argentina (Córdoba) with official data on the evolution of the pandemic (deaths and cases) and the outcome of the last elections. These panel data are used to study a town's decision to adopt NaIHS during the early phase of the pandemic, a period when concern about

[2] Hydroxychloroquine is probably the best-known example during the pandemic. Initially promoted by French medical researcher Didier Raoult, he was later accused by his peers of spreading false information about the benefits of the drug. 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 Clark Stanley, also called "The Rattlesnake King" who lost a legal case based on "misbranding" because the product he was selling did not contain enough snake oil; see, Gandhi, 2013).

[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 an ibuprofen treatment", *Clarín* May 7, 2020.

COVID-19 was at its highest and where differences in what strategy to adopt regarding an unusual, new drug lacking regulatory support can be expected to be strongest. 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) collected at the end of the pandemic. It elicits their views on NaIHS as well as their political beliefs. Importantly, the survey randomly exposes respondents to information describing the use of NaIHS despite the lack of a clinical trial (Treatment 1), successively adding information regarding the widespread use of NaIHS (Treatment 2) and its apparent effectiveness (Treatment 3). A fourth treatment exposes subjects to Treatment 1 and to the warnings against its use issued by regulators and professional groups (Treatment 4).

We document substantial adoption of this miracle cure: 184 towns (37% of our sample, where 81% of the population live) adopted NaIHS. We estimate that 64 towns (13% of the sample) eventually discontinued its use (even if our measure of "desadoption" is noisier). Our survey data reveal that almost 36% of those in our sample had direct exposure to NaIHS, because either they or a family member had consumed it. Another 41% knew somebody that had been treated with NaIHS, for a total of 77% overall exposure to NaIHS. There is evidence of learning in the two data sets, as there is more adoption when informal data suggesting NaIHS is effective becomes available. Ideology plays a central role in the diffusion of NaIHS: only right-wing individuals (and towns) learn from the evidence. A useful feature of our setting is that, in contrast to the US and Brazil, Argentina was governed during the pandemic by a center-left government, so adoption of NaIHS is done in defiance of political (as well as scientific) authority. In other words, while in Brazil and the US consumption of a "miracle drug" can be confused with political alignment on possibly extreme ideological lines, in Argentina it is closer to rational learning under high uncertainty.

Our paper is related to work on political economy during the pandemic, when vaccine hesitancy was a major concern (see COCONEL Group, 2020) and evidence emerged that ideology was associated with a host of factors, including perceptions of risk (Barrios & Hochberg, 2020), use of masks and social distance (see Allcott, et al., 2020, Grossman, et al, 2020, and Milosh, et al., 2021). Importantly, Galasso, et al., (2022), demonstrate that information about the benefits of vaccines (for example in avoiding infection or in protecting the economy) were effective in increasing vaccination rates even amongst respondents who had expressed anti-vaccine views. More generally, dellaVigna & Kim, (2022) and Cui, et al. (2021) find that the diffusion of laws and policies designed to stop COVID in the US was driven by political similarities across states rather than geographical proximity.

The spread of "miracle cures" is also connected to resistance to experts, an interesting dimension of populism (for evidence, see Bellodi, Morelli & Vannoni, 2021; for a model, see Di Tella & Rotemberg, 2019; for a review, see Guriev & Papaioannou, 2022). Albornoz, et al., (2022) find that, across 12 countries in Latin America, people's intended compliance with different health recommendations that are specific to the pandemic is reduced when it is attributed to experts (for a study of backlash against experts outside the pandemic, see Merkley, 2020). Our survey allows us to study beliefs in more detail, in particular the interplay between skeptic -or paranoid- beliefs and regulation. The evidence in Lewandowsky, et al., (2013), for example, suggests that paranoid beliefs correlate with the rejection of science, in contrast to conservative beliefs, which correlate with rejecting only scientific findings that are associated with greater regulation.

Prior work has documented the misuse of medical treatments.[5] A classic paper by Berndt, Pindyck & Azoulay (2003) shows that network effects, arising from informational herding, may lead to the prescription of a potentially inferior antiulcer drug. Meanwhile, the recent work of Agha & Zeltzer (2022) demonstrates how payments by pharmaceutical companies increase the prescription of blood thinners by targeted doctors and their peers to contraindicated patients. A fascinating paper by Cutler, Skinner, Stern & Wennberg (2019) connects misuse to beliefs. They study health care expenditures in the presence of physicians characterized by beliefs that are unsupported by clinical evidence (whom they call "cowboy doctors"). They find that their presence can explain 35% of end-of-life Medicare expenditures and that it is the absence of a financial penalty, rather than the presence of financial incentives, that mostly accounts for "cowboy" doctors' decisions. Chandra & Staiger (2020) study data on patients that suffered a heart attack and finds overuse of the main treatment (reperfusion therapy) to the point that one group of patients is harmed by the treatment. They find that smaller hospitals are particularly prone to have inaccurate beliefs about the effectiveness of their treatments, possibly due to a "general lack of systematic performance feedback and small samples" (see, also, Currie & MacLeod, 2017, 2020).[6]

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

[6] Similarly, the support of some doctors appears to have been important in the spread of NaIHS. See, for example, the testimony 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.

Outside the health context there is prior work, much of it in political science, studying the diffusion of policies with uncertain benefits (e.g., Walker, 1969, Volden, et al., 2008). An important paper 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 in their setting is not dissimilar to over-enthusiastic doctors with strong beliefs about clinically unproven drugs. Finally, sociologists have long emphasized the role of interpersonal communication in networks in the diffusion of new health technologies (Coleman, et al., 1957). Interestingly, Skinner & Staiger (2007) conclude that social or informational networks are associated with a failure to adopt several cost-effective technologies, ranging from hybrid corn and tractors in agriculture to beta-blockers in the treatment of heart attacks.[7]

An unusual aspect of this episode is that NaIHS was widely available even when the national regulator took the infrequent step of publicly announcing that it was not approved. 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 & Sun, 2008). Interestingly, 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.[8] Note that lack of regulatory approval means that we are studying diffusion in the absence of marketing efforts by the producer and quality certification by the state. Prior work on drugs such as beta blockers involves manufacturers that invest in a variety of marketing strategies to persuade consumers to buy it (see, for example, Azoulay, 2002 and Shapiro, 2018). Regulatory approval is also likely to affect product demand by providing third-party (State) endorsement of quality standards, both in terms of its production integrity and the claims made regarding the drug's effectiveness and side-effects.[9]

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[7] Recent examples emphasizing peer effects in health care decisions include Agha & Molitor (2018) and Chan (2021). A large literature in development studies how farmers learn about new technologies (e.g., Foster & Rosenzweig, 1995). Conley & Udry (2010) study how farmers in Ghana adjust fertilizer use to match the choices made by their more successful neighbors. Bold, et al., (2017) study low adoption of fertilizers when small farmers cannot distinguish authentic inputs. Work in this tradition uses different strategies to separate learning from peer effects (examples include Kremer & Miguel, 2007, on deworming and Oster & Thornton, 2012 on menstrual cups).

[8] 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). For a model where firm costs and experimental history affect the credibility of a new submission, see Carpenter and Ting (2007). Carpenter, (2002) studies FDA drug approval as a process of bureaucratic learning. There is growing interest in understanding the impact of scientific information (see, for example, the study of doctors and patient decisions before and after accessing the results of a randomized evaluation of the side effects associated with taking statin medication by Depalo, et al., 2019).

[9] These effects can increase use significantly: Berger, et al., (2021) document an increase in drug use of 40% over baseline following FDA approval and attribute it to the impact of certification by the FDA (rather than increased marketing efforts

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. In contrast to the US, the party in government at the time of the pandemic was on the left of the political spectrum.

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).[10] *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 Tecnología Médica, ANMAT*) did not approve the use of NaIHS during our sample period.[11] On April 2, 2020, however, the company obtained an authorization by the provincial government of Córdoba under an unusual

by the suppliers), in part because the increase is far larger than anything suggested by the literature on advertising and physician detailing (Iizuka and Jin, 2007 and Shapiro, 2018; for a review of quality certification see Dranove & Jin, 2010).

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

[11] Regulatory delay in the approval of new drugs is a standard concern (Peltzman 1973; Budish, Roin & Williams 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 & 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.

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.[12] 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).

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.[13] 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, 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. *ANMAT* only authorized a 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.

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[12] 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.

[13] 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, *ANMAT*'s 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.

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 began 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 began 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.[14] 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" 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

[14] 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).

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.[15] 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 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." [16]

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."[17] 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

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[15] 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).

[16] 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."

[17] 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.

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 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 had 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. Diffusion 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. We have data for 491 towns accounting for 99.67% of its population.

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 was used) into Desadopters (if adoption was temporary) and Forever-Adopters. Figure 4 splits the data along political lines. Ideology appears to play a role: the ratio of right wing to left wing towns is 12,33 (111/9) for Forever-Adopters, 8,14 (57/7) for Desadopters and 2,37 (216/91) for those that never adopt. 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).[18]

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,[19] (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 mobile phone usage, education and population was obtained from Argentina's 2010 national census, available at the National Institute of Statistics and Census.

[18] Skinner and Staiger (2007) report on the debate between Griliches, 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 importance of sociological factors, work in the two disciplines has showed little cross fertilization.

[19] 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.

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[20] 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.[21]

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 available for 444 towns. For 47 of the remaining 63 towns, we can impute political data from a neighboring area.[22] 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). *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 $NaIHS_{i,t}$ as explained in Figure 5: if town i never ordered NaIHS, the dummy variable takes the value of zero $\forall t$. If the town ordered NaIHS for the first time

[20] 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.

[21] 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).

[22] 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.

at time $t = \underline{t}$, the dummy takes the value of one at $t = \underline{t}$. If the town ordered NaIHS again at $t = \underline{t} + s$, then the dummy variable keeps turned on $\forall t > \underline{t}$. If the town never ordered NaIHS again, 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[23] at $t = \bar{t}$ the dummy is switched to zero. If the town did not reach the high number of deaths threshold $\forall t > \underline{t}$, we leave the dummy at 1, even when they did not order NaIHS again. This variable is the outcome used in our panel analysis. Note that adoption is measured with considerably more precision than desadoption.

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 wave of the pandemic (until December 2020 included) are *Early-Adopters*. Their complement, towns for which *NaIHS* got the value of one after 2020, are *Late-Adopters*.

III. b. Empirical Strategy:

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

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

where $NaIHS_{i,t}$ is town's i adoption of NaIHS in period t, ϕ_i and ϕ_t are geographic- and time- level fixed-effects, $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1 \right)$ and $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0 \right)$ are, respectively, weighted average of COVID deaths per capita of town's i neighbors $n(i)$ according to whether they were using NaIHS or not at time $t-1$ (where the neighbors $n(i)$ are all towns in the province weighted by their population and distance from i), , 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

[23] 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. Table A2 in Appendix A2 sets the threshold to the mean instead.

specification weights increase linearly with population, decay exponentially with distance and the daily data is collapsed into week periods. Figure 6 shows the set of weights of two different towns as examples to illustrate how these weights work in constructing neighbors.

As in Conley & Udry (2010), identification comes from the timing of bouts of new information: 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. 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 by setting each town to have a different set of "neighbors".[24] 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.[25]

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[24] Figure 6 shows two nearby towns with a different set of weights and, therefore, of neighbors.

[25] Conley & Udry's (2010) explain that social interactions effects could simply reflect that the underlying conditions of adoption are correlated between neighbors (our control could be interpreted as "growing deaths conditions" instead of "growing pineapple conditions"). As explained in Buera et al., (2011), our approach belongs to a family of binary non-linear choice models 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. Its first column shows that there is a strong positive association between *Right* and adopting NaIHS. The proportion of adopters goes from 25% to 40.9% when the measure of a town's political ideology goes from left to right. What is also strong is the association between being a right-wing town and *early* adopting NaIHS in the second column, with *Right* making the proportion of early adopters jump from 17.6% to 29.2%. Lastly, ideology also predicts sticking with NaIHS, with the proportion of forever adopters going from 15.5% in left-wing towns to 26.9% in right-wing towns. This suggests that political partisanship might have been the relevant heterogeneity at play during the key early periods of the diffusion of NaIHS.

Beyond political orientation, we further explore other determinants of both adoption and early adoption. 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.[26] More modern units typically adopt new technologies faster (e.g., Skinner & Staiger 2007), so we include *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. We also 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 spatial component that remains to be explained, which we explore in the panel specifications.

Learning and Peer Effects in the Diffusion of NaIHS

Table 3 estimates our main specification in full panel of 491 towns over 62 weeks. Its first column presents our panel specification with time fixed-effects but without geographic fixed-effects. The second column brings in the town fixed-effects. The third column adds town specific time trends.

[26] 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. Chandra et al., (2014) present evidence of early adoption of new technologies by higher quality hospitals. On the diffusion of disruptive technologies in the U.S. see Bloom, et al., (2021).

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).[27] Using the estimate from column 3, the long run effect is almost 5 times the short run effect.

Mechanism: Diffusion at the Onset of the Pandemic and the Role of Ideology

The S-curve pattern in adoption suggests that early adopters play an important role in the process of diffusion. The pandemic is an interesting setting as there is a clear early period where few alternatives were available and there was intense interest in learning about possible treatments for COVID-19. To investigate this, Table 4 separates our estimates for the first wave of the pandemic (August 2020 – December 2020) from the rest of our sample.[28]

Within panels, the coefficients in columns 1, 2 and 3 about learning from adopters are large and statistically significant and their counterparts in columns 4, 5 and 6 are smaller and generally statistically indistinguishable from zero. Between panels, the coefficients statistically differ from one another mostly. In particular, 0.003 is the p-value of a t-test between the coefficients in the second row of columns 1 and 4, 0.001 is the p-value between columns 2 and 5 and 0.000 is the p-value between columns 3 and 6. Altogether this implies that the learning coefficients in Table 3 were driven by the early period of diffusion.

We study the role of ideology in Table 5 separating our estimates for left and right-wing towns. As in Table 3 and 4, the first columns in each panel include time fixed-effects, the second columns geographic fixed effects and the third columns town specific time trends. Note that right-wing towns

[27] Appendix A provides several robustness checks. Table A3 in Appendix A3 uses a continuous version of *NaIHS*. Tables A4 in Appendix A4 use a sample of small towns and information on the institutions receiving the deliveries. Table A5 in Appendix A5 estimates Table 3 using 5 days as the unit for each period. Table A6 in Appendix A6 uses a socio-cultural definition of neighbors: regional football leagues.

[28] The robustness checks considered in the Appendix -see footnote 27- were also conducted for this section's sub-samples with similar results. Note one advantage of our estimates during the first wave is that there are only 12 desadopters (which is measured with more noise than adoption). The same results are obtained if desadoption is excluded from the analysis (see Appendix A7). Also, learning-by-doing plays no role (the diffusion literature has mostly concentrated in social rather than learning from one's own experience). Estimating learning-by-doing requires a larger number of desadopting towns.

still receive information from left-wing towns, since the latter are included in the weighted averages that the former take.[29]

The significant coefficients in second row's columns 1 to 3 contrast with the near-zero coefficients in columns 4 to 6. These coefficients are statistically different from each other, with a t-test between columns 1 and 4 displaying a p-value of 0.039, between 2 and 5 of 0.051 and between 3 and 6 of 0.032. This suggests that the early diffusion of NaIHS occurred in right-wing towns as they learn from the performance of other adopters.[30]

IV. Experimental Evidence on NaIHS Preference in a Survey of Individuals

We complement our study of diffusion during the first two waves of the pandemic (September 2020-November 2021) with an experimental survey conducted during September 2022. This survey collects information on knowledge of NaIHS, including prior consumption by the respondent and his/her immediate family, as well as the respondent's ideology and beliefs. The experimental section includes several information treatments (regarding NaIHS) and a treatment reminding subjects of the rejection of NaIHS on the part of experts and regulators.

IV.a. Data Description:

It is hard to pay subjects for large scale experimental studies in Argentina (for example through platforms like *MTurk* or *Lucid*). Instead, we engaged a local survey company that had some experience recruiting subjects using two channels: through its own Facebook group and via targeted Facebook ads. 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.

[29] Homophily, the phenomena of intragroup learning and peer effects, is a possibility that we do not explore in this paper.

[30] An alternative way to present these estimates is through an interaction with *Right* (see Table A8 in Appendix A8). Table A9 in Appendix A9 offers a robustness check with respect to the early period definition.

The company administered the survey through the software *QuestionPro,* where it was able to check the respondent's 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 (1,200 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 6.

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 from subtracting the value given to the performance of center-left former president Cristina Kirchner from the value given to center-right former president Mauricio Macri (question 10c). Strictly positive values correspond to the *Right* dummy, strictly negative values to the *Left* dummy and zero to the *Center* dummy. *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.[31] Similarly, the *Independence* question refers to whether the subject considers independence (versus obeyance to the rules) as an important quality in a child. We combine data on low trust, paranoid beliefs and consumption of traditional medicine into a variable labelled *Skeptic,* 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.[32] 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:

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[31] One complication with our interpretation is that non-adherence to guidelines appears to be higher amongst patients with access to medical expertise (see Finkelstein, et al., 2022).

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

From the start of the pandemic, newspapers reported that good results were being obtained, even in seriously ill patients. On August 5th, 2020, Clarín 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."

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** 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 7 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.

IV.b. Empirical 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. $NaIHS_i$ 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 three 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).

We are interested in the learning effect once we control for peer effects. Thus, we first identify a "pure" learning effect by looking at the difference between the effects of $T3_i$ versus $T2_i$. 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 learning 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 exactly comparable to the way we estimate learning or peer effects in our panel of towns. Note one advantage of these estimates: the treatments provide similar information to all individuals (whereas in the previous section it is conceivable that towns differ in the type of media exposure they choose).

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 8 uses our final sample of 4,861 observations to present some basic correlations between the pre-treatment variables and our three measures of demand for NaIHS. As in the cross-sectional cut of the panel, leaning right ideologically is positively correlated with all NaIHS outcome variables. Being classified as right takes the share of respondents who score 7 or more in the NaIHS Demand question from 51.1% to 58.1%, even after controlling for beliefs that are often correlated with political identification. Beyond our main heterogeneity of interest, trust (including trust in government) has a positive association with NaIHS. Valuing independence and being classified as a Cowboy patient has 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 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.

Learning and Peer Effects on Preferences for NaIHS

Table 9 (a) turn~~s~~ to experimental evidence. In all columns the coefficients on $T3_i$ and $T2_i$ go in the expected direction. The same is true for the difference ($T3_i - T2_i$) 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. This pure learning effect is significant at the 5% level or less in all specifications. To get a sense of the size of these coefficients, consider Figure 7 (a). A baseline of 51.7% of people exposed to the control condition scores 7 or more in the NaIHS demand question. To this we can add Table 2's column 2 $T2_i$ coefficient of 0.020 to reach 53.7% in the group treated with the popularity treatment. Or we can add 0.073 to achieve 59% in the group treated with the joint treatment. 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 9 (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. The last bar on Figure 7 (a) shows that once one adds the -0.067 coefficient to the aforementioned 51.7% baseline, one obtains that 45% of subjects primed with the regulator's ban information answer with 7 or more the NaIHS demand question.

Mechanism: The Role of Ideology and Other Beliefs

Given our hypothesis that heterogeneity in political ideology was important in the diffusion of NaIHS, Table 10 (a) restricts survey's final sample to right-wing individuals in columns 1 to 3 and to Left-wing individuals in columns 4 to 7. The $T3_i - T2_i$ coefficient shows that most of the "pure" learning comes from right-wing respondents: as in the panel of towns, the significant results in columns 1 to 3 contrast with the statistically zero coefficients in columns 4 to 7. Moreover, these coefficients are statistically different between them, with a p-value of 0.024 between columns 1 and 5, 0.009 between columns 2 and 6 and 0.501 between columns 3 and 7.

Figure 7 (b) gives a sense of the magnitudes. In the control condition, 54.4% of right-wing subjects score 7 or more in the NaIHS demand question, remaining constant after reading the popular treatment (T2-Popular). After reading information that NaIHS is both popular and seems effective (T3-Joint), 65.0% of right-wing subjects demand NaIHS. In contrast, 52% of left wingers demand NaIHS in the control condition, increasing to 55.8% after reading that it is popular. After reading information that NaIHS is both popular and appears to be effective, 56.6% of left-wing subjects demand NaIHS. Statistically speaking, right and left-wing individuals start from the same baseline (p-value 0.412), the popularity treatment makes these means even more similar (p-value 0.646), but the effectiveness treatment opens a gap between them (p-value 0.001). We interpret these findings as *Right* people mainly being influenced by the perceived effectiveness of the miracle cure rather than by their peers, while left-wing individuals tend to behave in the opposite way.[33]

Table 10 (b) does the same *Right-Left* split but regarding the regulation treatment. Though it seems that right-wing subjects are not affected by the regulatory treatment (T4-Regulation), while left-wing subjects are, the coefficients are not statistically different from each other. The p-value between columns 1 and 5 is 0.4550, between columns 2 and 6 is 0.1312, and between columns 3 and 7 is 0.1151. The last two bars in Figure 7 (b) show this result for *NaIHS Fan*: once exposed to the regulator's ban, 51.3% of right-wing individuals (from a 54.4% baseline) and 42.6% of left-wing individuals (from a 52.0% baseline) give NaIHS a score of 7 or more. There is a statistical difference between these means (p-value 0.004).

An interesting partition in the data uses the questions on unusual beliefs included in our survey (paranoid, trust in scientists, consumption of traditional medicine, etc). Including the constructed variable *Skeptic* reveals that the interaction coefficients associated with the regulation treatment are

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[33] A similar result is obtained by interacting the treatments with *Right*. See Appendix's B Table B1 and B2.

statistically different from each other. Specifically, in Table B3 of Appendix B we show that skeptics individuals increase their demand of NaIHS relative to non-skeptic individuals when primed with the regulator's ban. This is true even after controlling for the *Right x T4* and *Left x T4* interactions (given that skeptics can be found on both sides of the political aisle: only 58.2% of skeptics are right-wing individuals).[34]

V. Conclusions

We study the diffusion of a new, unproven technology in a high-stake setting. We focus on the case of nebulized ibuprofen, which spread throughout Argentina as a "miracle cure" against COVID-19 despite a complete lack of clinical evidence and many public warnings against its use issued by the federal regulator and professional societies. We document that, by the end of the pandemic, it had been administered to at least 99,453 COVID-19 patients. Such widespread diffusion, 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 ideology in affecting NaIHS adoption and the role of regulation (in contrast to the US and Brazil, the Argentine center-left government during the pandemic was opposed to NaIHS).

Our paper exploits two new 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 at the end of the pandemic. In both data sets being on the right of the political spectrum is correlated with demand for NaIHS.

Our main result is that there is 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. The two data sets use different identification strategies. Using our panel of towns, we exploit the timing of COVID

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[34] As a check on the mechanism, we included a question about conspiratorial beliefs specifically 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. Oostrom (2024) finds that when a drug trial is sponsored by the drug's manufacturer the results are more effective than when the trial is not sponsored by the drug's manufacturer.

related deaths in towns as opportunities for information transmission. Our survey allows us to recover causal effects through random assignment of information treatments.

We study heterogeneous effects. During the first wave of the pandemic, towns governed by the center-right political party learn, in the sense that they are more likely to adopt NaIHS when neighboring towns that have adopted do well in terms of having fewer COVID-19 deaths. No such effects are observable in towns governed by the left (there is weak evidence that they adopt more when neighbors adopt, independently of whether they are doing well). Similarly, in the survey, right-wing 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.

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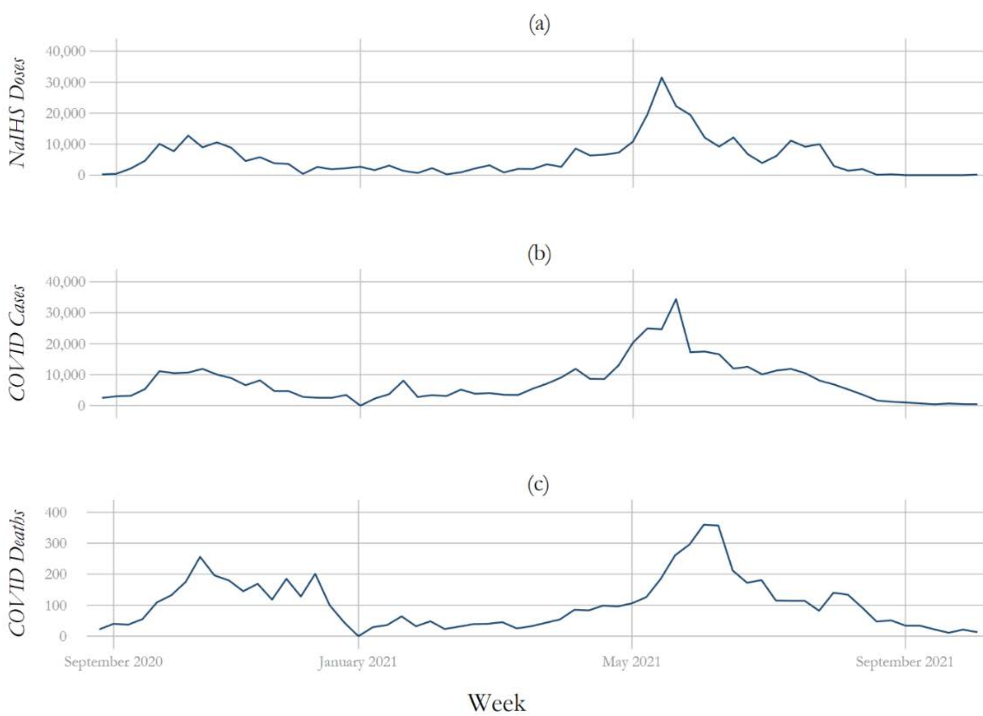
Figure 1. Delivery of NaIHS through "Helmet"

Source: "Coronavirus en Argentina: investigadores cordobeses prueban con éxito un tratamiento con ibuprofeno." *Clarín.*

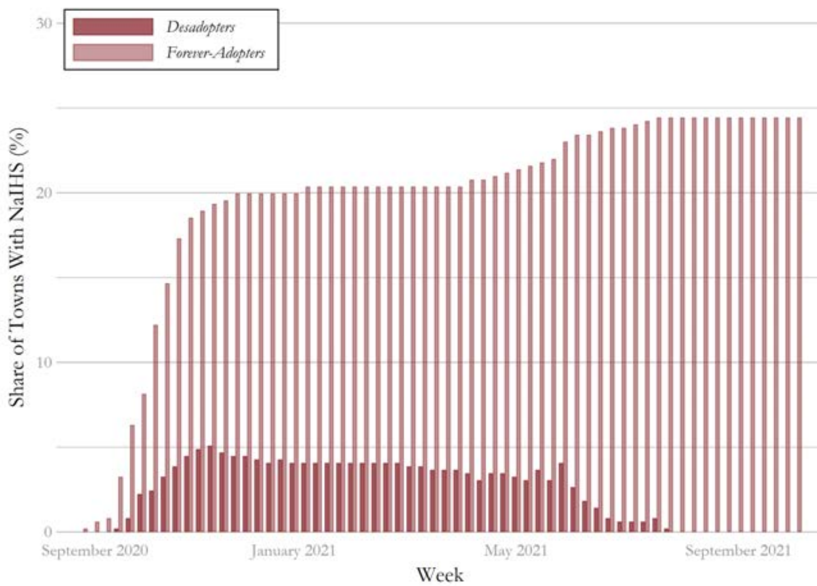
Figure 2. COVID-19 Pandemic in the Province of Córdoba

NaIHS Doses, COVID Cases and COVID Deaths



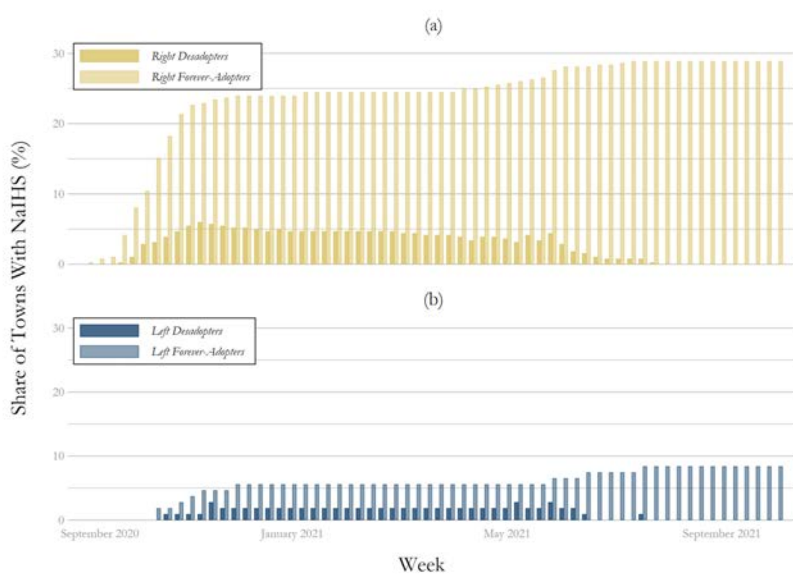
Notes: Final sample consists of 491 towns in the province of Córdoba over 62 weeks. Official data on COVID-19 cases and deaths at the town level was obtained from the Center of Emergency Operations (C.O.E.). Data on deliveries was provided by *Química Luar.*

Figure 3. NaIHS Diffusion in the Province of Córdoba



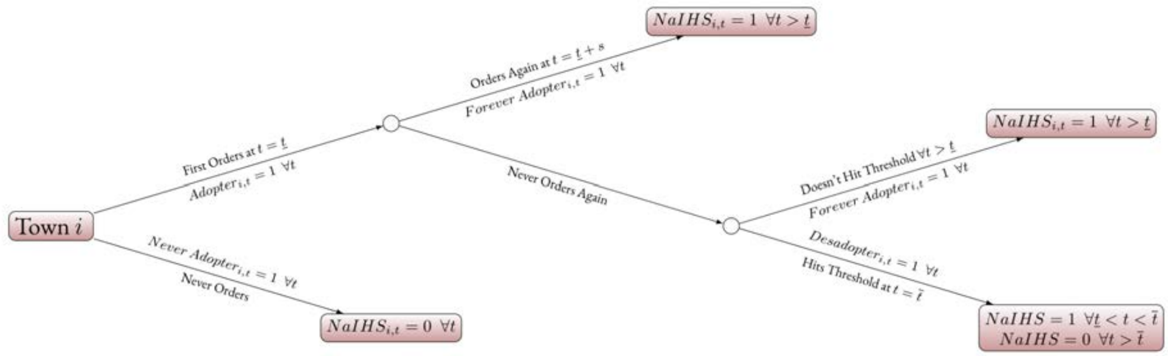
Notes: Final sample consists of 491 towns in the province of Córdoba over 62 weeks. Towns are all initially classified as N*on-Adopters*. A town is classified as an *Adopter* when it orders NaIHS for the first time. Within *Adopters,* if the town keeps demanding NaIHS, it is classified as *Forever-Adopter*. But if the town does not order NaIHS again despite accumulating "enough" COVID deaths, it is classified as a *Desadopter* ("enough" is a threshold that 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 yield an *Adopters* bar (omitted).

Figure 4. NaIHS Diffusion in the Province of Córdoba for Right-Wing and Left-Wing Towns



Notes: Final sample consists of 491 towns in the province of Córdoba over 62 weeks. Towns are all initially classified as N*on-Adopters*. A town 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 does not order NaIHS again despite accumulating "enough" COVID deaths, it is classified as a *Desadopter* ("enough" is a threshold that 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 yield an *Adopters* bar (omitted). A town is right-wing if Macri got a higher percentage of votes than Fernández in 2019 presidential election and left-wing otherwise. There are 384 right-wing towns and 107 left-wing towns. The share is calculated within towns of the same political alignment.

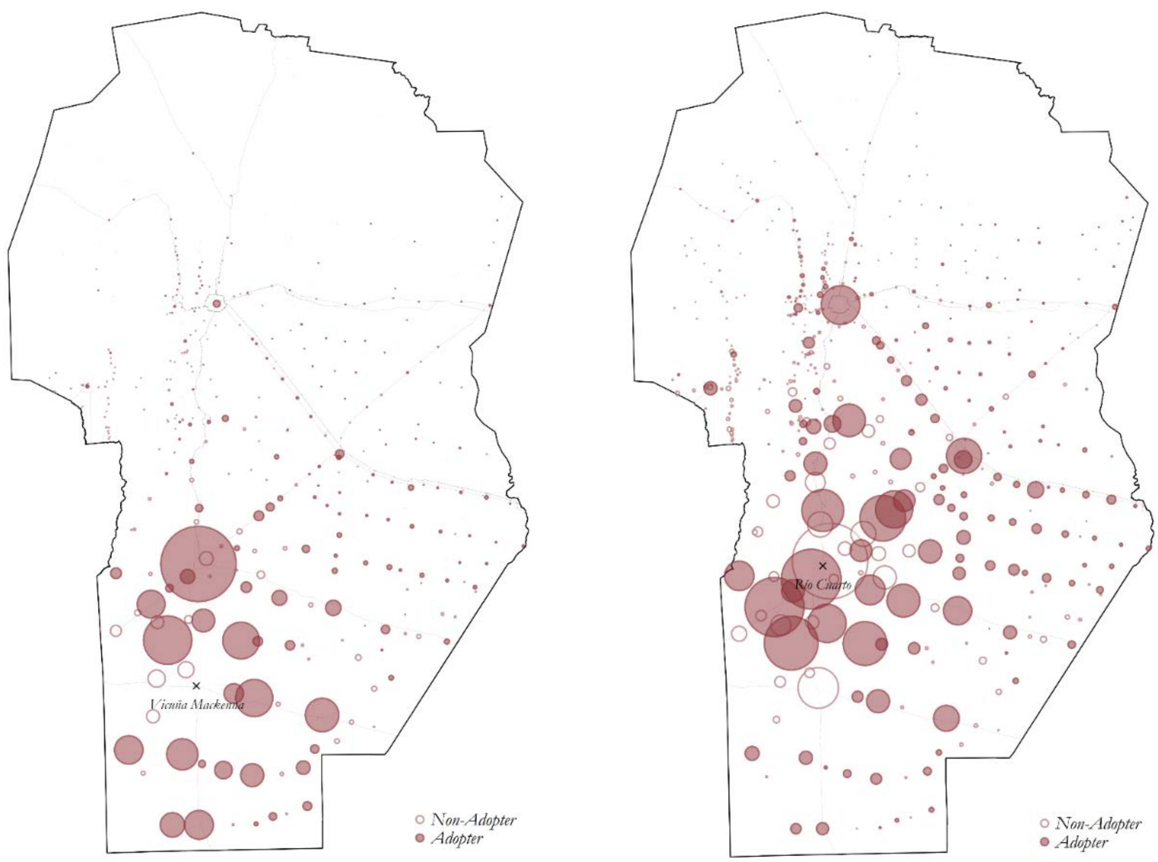
Figure 5. $NaIHS_{i,t}$, $Adopter_{i,t}$, $Never\ Adopter_{i,t}$, $Forever\ Adopter_{i,t}$ and $Desadopter_{i,t}$ Definition



Notes: $NaIHS_{i,t}$ is a time-varying-town-specific dummy variable and is the outcome variable used in our panel analysis. $Adopter_{i,t}$, $Never\ Adopter_{i,t}$, $Forever\ Adopter_{i,t}$ and $Desadopter_{i,t}$ summarize this information in the cross-section.

Figure 6. The Influence of Distance and Population on Neighbor's Definition Weights for Two Close by Towns.

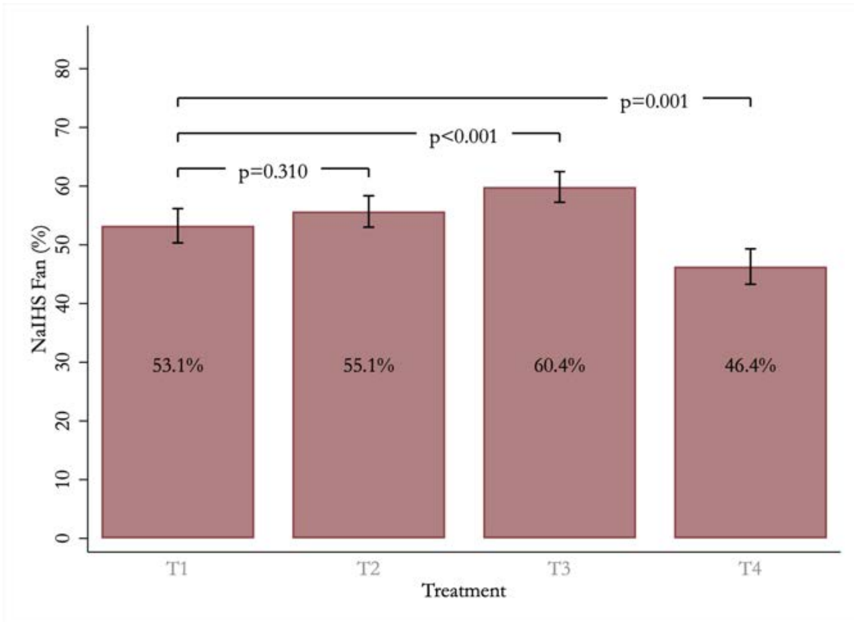
(a) Town of Vicuña Mackenna *(b) Town of Río Cuarto*



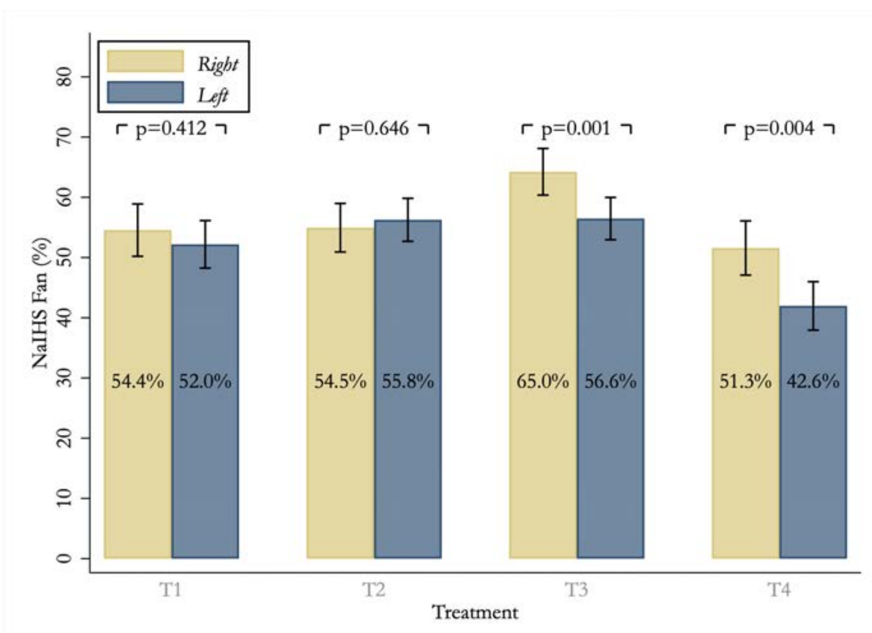
Notes: Final sample consists of 491 towns in the province of Córdoba over 62 weeks. Gray lines are the main routes. Towns are all initially classified as N*on-Adopters*. A town is classified as an *Adopter* when it orders NaIHS for the first time. Weights increase linearly with population and decay exponentially with distance. The distance between Vicuña Mackenna and Río Cuarto is 86.6 km.

Figure 7. Average Preference for NaIHS in Survey of Individuals.

(a) Control, Peer, Learning and Regulation Treatments



(b) Control, Popular, Joint and Regulation Treatments for Right-Wing and Left-Wing Individuals



Notes: Final sample consists of 4,861 individuals who spent more than 5 and less than 60 minutes answering the survey and who we did not geocode to be outside of Argentina. Conditional means for $NaIHS\ Fan_i$ are presented in bars. $NaIHS\ Demand_i$ 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 $NaIHS\ Demand_i$ question. *T1* refers to T1-Control, *T2* refers to T2-Popular, *T3* to T3-Joint and *T4* refers to T4-Regulation. *Right* is a dummy variable taking the value of 1 when the respondent ranks Macri higher than Kirchner. Confidence intervals at the 95%. P-values come from t-tests of conditional means.

Table 1. Summary Statistics in Panel of Towns

	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	131	0.27	0.44	0.00	1.00
Late-Adopters	53	0.11	0.31	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
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: Final 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 eighteen weeks of our sample. Otherwise, they are classified as *Late-Adopters*.

Table 2. NaIHS Adoption Cross-Sectional Correlations in Panel of Towns

	(1) Adopter	(2) Early-Adopter	(3) Forever-Adopter
Right	0.159***	0.116***	0.114***
	(0.045)	(0.038)	(0.039)
Distance to Córdoba (100 kms.)	0.135***	0.138***	0.101***
	(0.026)	(0.026)	(0.027)
Distance to Hospital (100 kms.)	-0.088	-0.075	-0.106
	(0.104)	(0.104)	(0.098)
Mobile Phones	-0.002	-0.001	-0.002
	(0.002)	(0.001)	(0.002)
College	0.001	0.004	-0.002
	(0.005)	(0.004)	(0.004)
Municipality	0.406***	0.288***	0.287***
	(0.052)	(0.052)	(0.052)
City	0.662***	0.538***	0.570***
	(0.058)	(0.077)	(0.074)
Population (10,000 habitants)	0.006	0.046	-0.013
	(0.052)	(0.070)	(0.074)
Cumulative Cases	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Cumulative Deaths	0.000	0.001	0.003
	(0.002)	(0.003)	(0.003)
Observations	491	491	491
Moran's Test	0.028	0.014	0.017
p-value	0.000	0.000	0.000
Baseline	0.250	0.176	0.155

Notes: Final 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 eighteen weeks of our sample. Otherwise, they are classified as *Late-Adopters*. Baseline refers to the value the outcome variable takes when all variables are at means but *Right*, which is at 0. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3. NaIHS Adoption in Panel of Towns

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.973***	0.860***	0.788***
	(0.002)	(0.010)	(0.011)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.004***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.031*	0.032	0.043**
	(0.018)	(0.020)	(0.021)
$\overline{NaIHS}_{n(i),t-1}$	0.017**	0.010	0.008
	(0.008)	(0.013)	(0.018)
Observations	29950	29950	29950
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Final 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. All the controls in Table 2 included here as well as period fixed effects. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4. NaIHS Adoption in Panel of Towns During Early and Late Period of Diffusion

	Dependent variable: $NaIHS_{i,t}$					
		Early Period			*Late Period*	
	(1)	(2)	(3)	(4)	(5)	(6)
$NaIHS_{i,t-1}$	0.947***	0.776***	0.565***	0.981***	0.882***	0.661***
	(0.006)	(0.009)	(0.015)	(0.002)	(0.016)	(0.033)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.005***	-0.006***	-0.009***	-0.001**	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.040	0.072*	0.052	0.028	0.026	0.029
	(0.031)	(0.038)	(0.047)	(0.023)	(0.026)	(0.028)
$\overline{NaIHS}_{n(i),t-1}$	0.015	0.037*	0.058*	0.019***	0.025	0.018
	(0.014)	(0.022)	(0.032)	(0.006)	(0.024)	(0.043)
p-val *Early* vs. *Late*	-	-	-	0.003	0.001	0.000
Observations	8346	8346	8346	21113	21113	21113
Town Specific Trend	No	No	Yes	No	No	Yes
Town FE	No	Yes	Yes	No	Yes	Yes

Notes: Columns (1)-(3) include sub-sample of 491 towns in the province of Córdoba over the initial eighteen weeks from final sample of 62 weeks. Columns (4)-(6) include sub-sample of 491 towns in the province of Córdoba past the initial eighteen weeks from final sample of 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. All the controls in Table 2 included here as well as period fixed effects. p-val *Early* vs. *Late* refers to the p-value from testing the equality of coefficients of $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ for early period versus late period. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5. NaIHS Adoption in Panel of Right-Wing and Left-Wing Towns During Early Diffusion

	Dependent variable: $NaIHS_{i,t}$					
	Right-Wing Towns			*Left-Wing Towns*		
	(1)	(2)	(3)	(4)	(5)	(6)
$NaIHS_{i,t-1}$	0.945***	0.768***	0.563***	0.935***	0.804***	0.484***
	(0.006)	(0.010)	(0.015)	(0.029)	(0.045)	(0.082)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.005***	-0.007***	-0.010***	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.053	0.094**	0.071	0.008	-0.001	0.004
	(0.035)	(0.042)	(0.052)	(0.038)	(0.051)	(0.064)
$\overline{NaIHS}_{n(i),t-1}$	0.005	0.025	0.041	0.054*	0.081	0.110
	(0.017)	(0.025)	(0.035)	(0.028)	(0.055)	(0.089)
p-val *Right* vs. *Left*	-	-	-	0.039	0.051	0.032
Observations	6527	6527	6527	1819	1819	1819
Town Specific Trend	No	No	Yes	No	No	Yes
Town FE	No	Yes	Yes	No	Yes	Yes

Notes: Columns (1)-(3) include sub-sample of 384 right-wing towns over the initial eighteen weeks from final sample of 491 towns in the province of Córdoba over 62 weeks. Columns (4)-(6) include sub-sample of 107 left-wing towns over the initial eighteen weeks from final sample 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. All the controls in Table 2 included here as well as period fixed effects. A town is right-wing if Macri got a higher percentage of votes than Fernández in 2019 presidential election and left-wing otherwise. p-val *Right* vs. *Left* refers to the p-value from testing the equality of coefficients of $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ for right-wing towns versus left-wing towns. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6. Summary Statistics in 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
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 consists of 4,861 individuals who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina.

Table 7. Balance in 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)
N	1,123	1,329	1,355	1,054	2,452	2,478	2,177

Notes: Final sample consists of 4,861 individuals who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 8. NaIHS Preferences Correlations in Survey of Individuals

	(1) NaIHS Demand	(2) NaIHS Fan	(3) NaIHS Yes
Right	0.467***	0.070***	0.086***
	(0.117)	(0.019)	(0.020)
Left	-0.113	-0.009	0.001
	(0.125)	(0.020)	(0.020)
Raoult Bad System	0.074	-0.018	0.077***
	(0.091)	(0.015)	(0.015)
Distrusts Government	-0.209**	-0.042**	-0.026
	(0.102)	(0.017)	(0.017)
Distrusts Scientists	-0.444***	-0.072***	-0.049***
	(0.093)	(0.015)	(0.015)
Distrusts Business	-0.304***	-0.057***	-0.056***
	(0.090)	(0.015)	(0.015)
Pro Ruda	0.424***	0.064***	0.106***
	(0.090)	(0.015)	(0.015)
Cowboy	-0.426***	-0.073***	-0.029**
	(0.088)	(0.014)	(0.014)
Independence	-0.167*	-0.038***	-0.010
	(0.088)	(0.014)	(0.015)
Messi Better	0.188*	0.032*	0.054***
	(0.104)	(0.017)	(0.017)
Maradona Better	0.160	0.029	0.033*
	(0.115)	(0.019)	(0.019)
Religious	0.177**	0.058***	0.018
	(0.087)	(0.015)	(0.015)
Higher Education	-0.349***	-0.064***	-0.017
	(0.094)	(0.016)	(0.016)
Private Health Coverage	0.065	0.004	-0.019
	(0.111)	(0.019)	(0.019)
Public Health Coverage	0.052	0.001	-0.002
	(0.109)	(0.017)	(0.018)
Male	-0.155*	-0.010	0.043***
	(0.092)	(0.015)	(0.015)
Age	0.058***	0.006*	0.010***
	(0.019)	(0.003)	(0.003)
Age Sq. (100 years)	-0.054***	-0.004	-0.010***
	(0.018)	(0.003)	(0.003)
Buenos Aires	-0.076	-0.020	-0.021
	(0.125)	(0.021)	(0.021)
CABA	-0.429***	-0.094***	-0.077***
	(0.132)	(0.022)	(0.023)
Córdoba	0.341***	0.054**	0.005
	(0.126)	(0.021)	(0.021)
N	4,861	4,861	4,861
R-squared	0.050	0.062	0.042
Baseline	6.315	0.511	0.457

Notes: Final sample consists of 4,861 individuals who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. Baseline refers to the value the outcome variable takes when all variables are at means but *Right*, which is at 0. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 9. NaIHS Preferences in Survey of Individuals

(a) Popular and Joint Treatments

	(1) $NaIHS\ Demand_i$	(2) $NaIHS\ Fan_i$	(3) $NaIHS\ Yes_i$
$T3_i$	0.496***	0.073***	0.071***
	(0.118)	(0.019)	(0.020)
$T2_i$	0.278**	0.020	0.034*
	(0.119)	(0.020)	(0.020)
$T3_i - T2_i$	0.218	0.053	0.037
p-val	0.045	0.004	0.050
Baseline	6.392	0.531	0.474
N	4861	4861	4861

Notes: Final sample consists of 4,861 individuals who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. $NaIHS\ Demand_i$ 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 $NaIHS\ Demand_i$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $T2_i$ refers to T2-Popular, $T3_i$ to T3-Joint and $T3_i - T2_i$ combines them linearly by subtraction capturing a "pure" learning effect. p-val refers to the associated p-value of that linear combination. Baseline refers to the value the outcome variable takes when all variables are at means but *T2*, *T3* and *T4*, which are at 0. Controls include *T4* and all variables included in Table 8. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(b) Regulation Treatment

	(1) $NaIHS\ Demand_i$	(2) $NaIHS\ Fan_i$	(3) $NaIHS\ Yes_i$
$T4_i$	-0.385***	-0.067***	-0.036*
	(0.131)	(0.021)	(0.021)
Baseline	6.392	0.531	0.474
N	4861	4861	4861

Notes: Final sample consists of 4,861 individuals who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. $NaIHS\ Demand_i$ 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 $NaIHS\ Demand_i$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $T4_i$ refers to T4-Regulation. Baseline refers to the value the outcome variable takes when all variables are at means but *T2*, *T3* and *T4*, which are at 0. Controls include *T2*, *T3* and all variables included in Table 8. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 10. NaIHS Preferences in Survey of Right-Wing and Left-Wing Individuals

(a) Popular and Joint Treatments for Right-Wing and Left-Wing Individuals

	Right-Wing Individuals			*Left-Wing Individuals*		
	$NaIHS$ $Demand_i$	$NaIHS$ Fan_i	$NaIHS$ Yes_i	$NaIHS$ $Demand_i$	$NaIHS$ Fan_i	$NaIHS$ Yes_i
	(1)	(2)	(3)	(4)	(5)	(6)
$T3_i$	0.580***	0.105***	0.092***	0.442***	0.046*	0.060**
	(0.167)	(0.029)	(0.030)	(0.166)	(0.026)	(0.027)
$T2_i$	0.091	0.001	0.040	0.440***	0.037	0.034
	(0.169)	(0.030)	(0.030)	(0.167)	(0.026)	(0.027)
$T3_i - T2_i$	0.489	0.105	0.052	0.002	0.009	0.026
p-val	0.002	0.000	0.069	0.989	0.718	0.304
Baseline	6.596	0.544	0.499	6.218	0.520	0.450
p-val *Right* vs *Left*	-	-	-	0.024	0.009	0.501
N	2157	2157	2157	2704	2704	2704

Notes: Columns (1)-(3) include sub-sample of 2,157 right-wing individuals from final sample of 4,861 individual that consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. Columns (4)-(6) include sub-sample of 2,704 left-wing individuals from final sample of 4,861 individuals that consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. $NaIHS\ Demand_i$ 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 $NaIHS\ Demand_i$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $T2_i$ refers to T2-Popular, $T3_i$ to T3-Joint and $T3_i - T2_i$ combines them linearly by subtraction capturing a "pure" learning effect. p-val refers to the associated p-value of that linear combination. Baseline refers to the value the outcome variable takes when all variables are at means but *T2*, *T3* and *T4*, which are at 0. Controls include *T4* and all variables included in Table 8. An individual is right-wing if the respondent ranks from 1("Very bad president") to 5 ("Very good president") Macri higher than Kirchner and left-wing otherwise. p-val *Right* vs. *Left* refers to the p-value from testing the equality of coefficients of *T3-T2* for right-wing individuals versus left-wing individuals. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(b) Regulation Treatment for Right-Wing and Left-Wing Individuals

	Right-Wing Individuals			*Left-Wing Individuals*		
	$NaIHS$ $Demand_i$	$NaIHS$ Fan_i	$NaIHS$ Yes_i	$NaIHS$ $Demand_i$	$NaIHS$ Fan_i	$NaIHS$ Yes_i
	(1)	(2)	(3)	(4)	(5)	(6)
$T4_i$	-0.271	-0.031	0.003	-0.466***	-0.095***	-0.063**
	(0.190)	(0.031)	(0.031)	(0.181)	(0.028)	(0.028)
Baseline	6.596	0.544	0.499	6.218	0.520	0.450
p-val *Right* vs *Left*	-	-	-	0.455	0.131	0.115
N	2157	2157	2157	2704	2704	2704

Notes: Columns (1)-(3) include sub-sample of 2,157 right-wing individuals from final sample of 4,861 individuals that consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. Columns (4)-(6) include sub-sample of 2,704 left-wing individuals from final sample of 4,861 individuals that consists of people who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. $NaIHS\ Demand_i$ 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 $NaIHS\ Demand_i$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $T4_i$ refers to T4-Regulation. Baseline refers to the value the outcome variable takes when all variables are at means but *T2*, *T3* and *T4*, which are at 0. Controls include *T2*, *T3* and all variables included in Table 8. An individual is right-wing if the respondent ranks from 1("Very bad president") to 5 ("Very good president") Macri higher than Kirchner and left-wing otherwise. p-val *Right* vs. *Left* refers to the p-value from testing the equality of coefficients of *T4* for right-wing individuals versus left-wing individuals. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

[For Online Publication]

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 increases to 81 weeks. Table A1 replicates Table 3 under this new sample. Results are practically identical.

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

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.980*** (0.002)	0.883*** (0.009)	0.800*** (0.010)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.029* (0.016)	0.031* (0.017)	0.038** (0.019)
$\overline{NaIHS}_{n(i),t-1}$	0.015** (0.007)	0.009 (0.013)	0.007 (0.017)
Observations	39279	39279	39279
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Alternative non-trimmed sample of 491 Córdoba province's towns over 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. 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. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix A2: Robustness to threshold of outcome variable

This robustness check redefines the discrete outcome variable $NaIHS_{i,t}$. If a town did not reorder NaIHS after reaching a high number of deaths at $t = \bar{t}$, the dummy is set to zero. If the town never reached the high number of deaths threshold for $\forall t > \underline{t}$, the dummy remains at one, even if NaIHS was not reordered. Originally, that high number of deaths was based on the median deaths per capita when towns reordered. We now redefine it using the mean deaths per capita. Note that $\overline{NaIHS}_{n(i),t-1}$ $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ and $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ also needed to change. Coefficients remain stable across specifications. $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$ and $\overline{NaIHS}_{n(i),t-1}$ are not significant in any specification.

Table A2. NaIHS Adoption in Panel of Towns - Alternative Outcome Variable

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.973*** (0.002)	0.862*** (0.010)	0.792*** (0.010)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.004*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.024 (0.020)	0.026 (0.022)	0.036 (0.022)
$\overline{NaIHS}_{n(i),t-1}$	0.011 (0.008)	0.004 (0.013)	0.003 (0.019)
Observations	29950	29950	29950
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Final 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. All the controls in Table 2 included here as well as period fixed effects. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix A3: 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 A3 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 A3. NaIHS Adoption in Panel of Towns - Continuous Outcome Variable

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	1.019*** (0.001)	0.988*** (0.002)	0.944*** (0.020)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-3.248*** (1.220)	-2.172*** (0.783)	-3.178*** (1.002)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	63.790*** (22.975)	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)
Observations	29950	29950	29950
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Final sample consists of 491 towns in the province of Córdoba over 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. 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. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix A4: 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 A4a 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 A4b. Results are practically identical.

Table A4

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

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.973***	0.859***	0.787***
	(0.003)	(0.011)	(0.012)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.004***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.030	0.031	0.041*
	(0.018)	(0.021)	(0.022)
$\overline{NaIHS}_{n(i),t-1}$	0.022***	0.012	0.003
	(0.008)	(0.013)	(0.019)
Observations	28426	28426	28426
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Alternative small towns sample of 466 Córdoba province's towns 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. 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. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

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

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.974***	0.855***	0.789***
	(0.002)	(0.011)	(0.011)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.004***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.022	0.022	0.033
	(0.017)	(0.019)	(0.021)
$\overline{NaIHS}_{n(i),t-1}$	0.018**	0.010	0.006
	(0.008)	(0.013)	(0.019)
Observations	28791	28791	28791
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Alternative town-specific deliveries sample of 472 Córdoba province's towns 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. 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. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix A5: 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 A5 replicates Table 3 under this new sample. Results are practically identical.

Table A5. NaIHS Adoption in Panel of Towns – 5 Days Period

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.981*** (0.002)	0.898*** (0.007)	0.843*** (0.008)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.004*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.021 (0.015)	0.021 (0.015)	0.025 (0.015)
$\overline{NaIHS}_{n(i),t-1}$	0.009 (0.006)	-0.000 (0.011)	0.012 (0.013)
Observations	41735	41735	41735
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Alternative 5 days periods sample of 491 Córdoba province's towns over 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. 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. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix A6: 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 A6.

Table A6. NaIHS Adoption in Panel of Towns – Soccer League Neighbors

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.9747***	0.8360***	0.7101***
	(0.0024)	(0.0149)	(0.0170)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.0005***	-0.0004***	-0.0004*
	(0.0001)	(0.0002)	(0.0002)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.0013	0.0043	0.0097
	(0.0071)	(0.0085)	(0.0088)
$\overline{NaIHS}_{n(i),t-1}$	0.0094***	0.0143*	0.0172
	(0.0027)	(0.0086)	(0.0121)
Observations	27637	27637	27637
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Final 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. These weighted averages are calculated for towns within the same soccer league. There are 18 soccer leagues in the province of Córdoba. 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. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix A7: Robustness to desadoption

$NaIHS_{i,t}$ 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. Here instead, once the dummy takes the value of 1 in any period, it remains 1 thereafter regardless of future reorders or death counts. This takes desadoption (which might be measured with noise given our definition) out of the picture. Table 3 is replicated under this new definition in Table A7 (a) and Table 4 in Table A7 (b).

Table A7

(a) NaIHS Adoption in Panel of Towns – No Desadopters

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.984*** (0.002)	0.900*** (0.006)	0.834*** (0.005)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.067** (0.027)	0.065*** (0.024)	0.072*** (0.024)
$\overline{NaIHS}_{n(i),t-1}$	0.015* (0.009)	-0.000 (0.014)	0.008 (0.017)
Observations	29950	29950	29950
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Final 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 does not turn off to zero. $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ 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. All the controls in Table 2 included here as well as period fixed effects. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(b) NaIHS Adoption in Panel of Towns During Early and Late Period of Diffusion – No Desadoption

	***Dependent variable**: $NaIHS_{i,t}$*					
		Early Period			*Late Period*	
	(1)	(2)	(3)	(4)	(5)	(6)
$NaIHS_{i,t-1}$	0.959***	0.799***	0.590***	0.982***	0.882***	0.661***
	(0.005)	(0.006)	(0.008)	(0.002)	(0.016)	(0.033)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.005***	-0.007***	-0.009***	-0.001**	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.051	0.071**	0.045	0.028	0.026	0.029
	(0.033)	(0.033)	(0.041)	(0.023)	(0.026)	(0.028)
$\overline{NaIHS}_{n(i),t-1}$	0.018	0.041*	0.060*	0.019***	0.025	0.018
	(0.014)	(0.023)	(0.033)	(0.006)	(0.024)	(0.043)
p-val *Early* vs. *Late*	-	-	-	0.003	0.001	0.000
Observations	8346	8346	8346	21113	21113	21113
Town Specific Trend	No	No	Yes	No	No	Yes
Town FE	No	Yes	Yes	No	Yes	Yes

Notes: Columns (1)-(3) include sub-sample of 491 towns in the province of Córdoba over the initial eighteen weeks from final sample of 62 weeks. Columns (4)-(6) include sub-sample of 491 towns in the province of Córdoba past the initial eighteen weeks from final sample of 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 does not turn off to zero in the early period. In the late period it (i) does not turn off to zero if the town ordered NaIHS again or did not accumulate enough COVID deaths to justify ordering again and (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. All the controls in Table 2 included here as well as period fixed effects. p-val *Early* vs. *Late* refers to the p-value from testing the equality of coefficients of $\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$ for early period versus late period. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix A8: Robustness to right-wing and left-wing heterogeneity

Table A8. NaIHS Adoption in Panel of Towns - Interaction with Right-Wing

	(1) $NaIHS_{i,t}$	(2) $NaIHS_{i,t}$	(3) $NaIHS_{i,t}$
$NaIHS_{i,t-1}$	0.935***	0.804***	0.484***
	(0.029)	(0.044)	(0.081)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.004)
$Right_i$	0.017	-0.041***	0.050
	(0.026)	(0.013)	(0.033)
$Right_i\ x\ \left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.006**	-0.006*	-0.009**
	(0.003)	(0.003)	(0.004)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.008	-0.001	0.004
	(0.038)	(0.051)	(0.064)
$Right_i\ x\ \left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.046	0.095	0.068
	(0.051)	(0.066)	(0.082)
$\overline{NaIHS}_{n(i),t-1}$	0.054*	0.081	0.110
	(0.028)	(0.054)	(0.088)
$Right_i\ x\ \overline{NaIHS}_{n(i),t-1}$	-0.049	-0.056	-0.070
	(0.033)	(0.060)	(0.095)
Observations	8346	8346	8346
Town Specific Trend	No	No	Yes
Town FE	No	Yes	Yes

Notes: Sample consists of 491 towns in the province of Córdoba over the initial eighteen weeks from final sample of 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. All the controls in Table 2 included here as well as period fixed effects. *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. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix A9: Robustness to early-adoption definition

In the main text, the time threshold that separates early from late-adoption is week 18 in our panel (last week of December 2020). This also determines the split between the early and late periods in Table 4. Table A9 offers a robustness check with respect to this definition, with panel (a) making it one week earlier and panel (b) making it one week later. Results remain largely unchanged.

Table A9

(a) NaIHS Adoption in Panel of Towns – (Earlier) Adoption Definition

	***Dependent variable**: $NaIHS_{i,t}$*					
	Early Period			*Late Period*		
	(1)	(2)	(3)	(4)	(5)	(6)
$NaIHS_{i,t-1}$	0.943***	0.772***	0.541***	0.982***	0.884***	0.667***
	(0.006)	(0.010)	(0.016)	(0.002)	(0.015)	(0.032)
$(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1)$	-0.005***	-0.006***	-0.009***	-0.001**	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
$(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0)$	0.049	0.073*	0.044	0.028	0.026	0.029
	(0.031)	(0.039)	(0.048)	(0.023)	(0.026)	(0.028)
$\overline{NaIHS}_{n(i),t-1}$	0.016	0.038*	0.056*	0.018**	0.021	0.018
	(0.015)	(0.023)	(0.033)	(0.006)	(0.022)	(0.039)
Observations	7855	7855	7855	21604	21604	21604
Town Specific Trend	No	No	Yes	No	No	Yes
Town FE	No	Yes	Yes	No	Yes	Yes

Notes: Columns (1)-(3) include sub-sample of 491 towns in the province of Córdoba over the initial seventeen weeks from final sample of 62 weeks. Columns (4)-(6) include sub-sample of 491 towns in the province of Córdoba past the initial seventeen weeks from final sample of 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. All the controls in Table 2 included here as well as period fixed effects. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(b) NaIHS Adoption in Panel of Towns – (Later) Adoption Definition

	Dependent variable: $NaIHS_{i,t}$					
	Early Period			*Late Period*		
	(1)	(2)	(3)	(4)	(5)	(6)
$NaIHS_{i,t-1}$	0.950***	0.778***	0.581***	0.981***	0.882***	0.664***
	(0.006)	(0.009)	(0.015)	(0.002)	(0.015)	(0.033)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 1\right)$	-0.005***	-0.006***	-0.008***	-0.001**	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
$\left(\overline{Deaths}_{n(i),t-1} \mid NaIHS_{n(i),t-1} = 0\right)$	0.040	0.073**	0.063	0.028	0.026	0.029
	(0.030)	(0.037)	(0.044)	(0.023)	(0.026)	(0.028)
$\overline{NaIHS}_{n(i),t-1}$	0.014	0.033	0.059*	0.020***	0.026	0.017
	(0.014)	(0.022)	(0.031)	(0.006)	(0.025)	(0.049)
Observations	8837	8837	8837	20622	20622	20622
Town Specific Trend	No	No	Yes	No	No	Yes
Town FE	No	Yes	Yes	No	Yes	Yes

Notes: Columns (1)-(3) include sub-sample of 491 towns in the province of Córdoba over the initial nineteen weeks from final sample of 62 weeks. Columns (4)-(6) include sub-sample of 491 towns in the province of Córdoba past the initial nineteen weeks from final sample of 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. All the controls in Table 2 included here as well as period fixed effects. All regression include a constant. Standard errors clustered at the town level in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix B: Survey's Additional Tables Appendix

Table B1. NaIHS Preferences in Survey of Individuals - Interactions with Right-Wing

	(1) $NaIHS\ Demand_i$	(2) $NaIHS\ Fan_i$	(3) $NaIHS\ Yes_i$
$Right_i$	-0.376	-0.019	-0.453***
	(0.976)	(0.165)	(0.164)
$T3_i$	0.580***	0.105***	0.092***
	(0.167)	(0.029)	(0.030)
$Right_i\ x\ T3_i$	-0.138	-0.059	-0.031
	(0.235)	(0.039)	(0.040)
$T2_i$	0.091	0.001	0.040
	(0.169)	(0.030)	(0.030)
$Right_i\ x\ T2_i$	0.349	0.037	-0.006
	(0.238)	(0.040)	(0.040)
$Right_i\ x\ (T3_i - T2_i)$	-0.487	-0.096	-0.025
p-val	0.025	0.010	0.503
Baseline (T2 = 0)	6.304	0.517	0.464
N	4861	4861	4861

Notes: Final sample consists of 4,861 individuals who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. $NaIHS\ Demand_i$ 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 $NaIHS\ Demand_i$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $T2_i$ refers to T2-Popular, $T3_i$ to T3-Joint and $T3_i - T2_i$ combines them linearly by subtraction capturing 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 8. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table B2. NaIHS Preferences in Survey of Individuals - Interactions with Right-Wing

	(1) $NaIHS\ Demand_i$	(2) $NaIHS\ Fan_i$	(3) $NaIHS\ Yes_i$
$Right_i$	-0.455	-0.023	-0.456***
	(0.979)	(0.166)	(0.165)
$T4_i$	-0.467***	-0.095***	-0.063**
	(0.181)	(0.028)	(0.028)
$Right_i\ x\ T4_i$	0.195	0.063	0.066
	(0.262)	(0.042)	(0.042)
Baseline	6.388	0.529	0.463
N	4861	4861	4861

Notes: Final sample consists of 4,861 individuals who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. $NaIHS\ Demand_i$ 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 $NaIHS\ Demand_i$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $T4_i$ refers to T4-Regulation. *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 8. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table B3. NaIHS Preferences in Survey of Individuals - Interactions with Skeptics

	(1) $NaIHS\ Demand_i$	(2) $NaIHS\ Fan_i$	(3) $NaIHS\ Yes_i$
$Skeptic_i$	-1.230	-0.204	-0.116
	(1.010)	(0.168)	(0.169)
$T4_i$	-0.713***	-0.122***	-0.055*
	(0.202)	(0.032)	(0.032)
$Skeptic_i\ x\ T4_i$	0.528*	0.088**	-0.003
	(0.271)	(0.043)	(0.043)
Baseline	6.551	0.545	0.475
N	4861	4861	4861

Notes: Final sample consists of 4,861 individuals who spent more than 5 minutes (and less than 60) answering the survey and their geocode was inside Argentina. $NaIHS\ Demand_i$ 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 $NaIHS\ Demand_i$ question. $NaIHS\ Yes_i$ is a dummy variable taking the value of 1 if the respondent supports a campaign for the approval of NaIHS. $T4_i$ refers to T4-Regulation. *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*, *Right x T4*, and all variables included in Table 8. All regression include a constant. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix C: 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).
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).

    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]