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Health shocks and their long-lasting impact on health behaviors: Evidence from the 2009 H1N1 pandemic in Mexico

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ABSTRACT

Worldwide, the leading causes of death could be avoided with health behaviors that are low-cost but also difficult to adopt. We show that exogenous health shocks could facilitate the adoption of these behaviors and provide long-lasting effects on health outcomes. Specifically, we exploit the spatial and temporal variation of the 2009 H1N1 influenza pandemic in Mexico and show that areas with a higher incidence of H1N1 experienced larger reductions in diarrhea-related cases among young children. These reductions continue even three years after the shock ended. Health improvements and evidence of information seeking via Google searches were consistent with changes in hand washing behaviors. Several robustness checks validate our findings and mechanism.

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1. Introduction

Worldwide, the adoption of low-cost technologies could improve health outcomes and save lives. For example, regular physical activity reduces the risk of diabetes; condoms help reduce the spread of sexually transmitted diseases, including HIV; reductions in cigarette consumption help avoid pulmonary cancer; and hand washing with soap prevents gastrointestinal diseases. However, despite their effectiveness, the take up rates of these products or

behaviors is very low (Dupas, 2011). For instance, while the role of hand washing as an effective way to reduce gastrointestinal diseases has been known for more than a century (Koplik, 1902),² in developing countries, only 30% of household members wash their hands before preparing food or after defecation. In some countries the rate is as low as zero (World Bank, 2005; Chase and Do, 2010). Moreover, intensive small-scale interventions show significant reductions in diarrhea (e.g., Ejemot-Nwadiaro et al., 2008; Luby et al., 2004; Luby et al., 2005),³ but scaling up similar inter-

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² For example, Koplik (1902) summarizes the research of the previous decade and recommends the “scrupulously” cleaning of hands and nails (“with brush and file”) after changing a diaper for nurses handling a newborn. Mothers, he added, “should carefully cleanse their hands before feeding the baby” (p. 321). The rationale for this hygiene practice was also well understood “since this way contamination of the infant’s food with fecal bacteria is avoided” (p. 46).

³ Common interventions to reduce diarrhea have focused on providing infrastructure or information. Infrastructure projects focus on providing safe water supplies and sanitation (e.g., Pattanayak et al., 2009; Kremer et al., 2011), micronutrients or vaccinations (Dowling and Yap 2014). Information-based interventions focus on hygiene education and community-led total sanitation (CLTS) (Dowling and Yap 2014). Also, recent papers have discussed the external validity of these studies. See Hammer and Spears (2016) for a discussion on whether the sites where village sanitation projects take place might be likely to exhibit large effects.

ventions does not (e.g., Meredith et al., 2013; Galiani et al., 2012).⁴ Understanding the barriers for the adoption of these preventive behaviors and products is an urgent issue in health and development economics.

A growing literature in economics is studying the role that information plays on health behaviors as a salient input in the production of health outcomes (Cawley and Ruhm 2011).⁵ In particular, an emerging conclusion suggests that the mere provision of information might not matter (e.g., smokers do know that smoking is harmful and may even overestimate the risk of smoking, Viscusi, 1990). Rather, the emphasis seems to be on *when* information alters the decision-making process (Luoto and Carman 2014). Our paper contributes to this literature by showing that health shocks such as disease outbreaks can operate as “natural nudges” that facilitate changes in health behaviors that lead to improvements in health outcomes, and that these types of shock-induced improvements can have long-lasting effects.

In particular, we illustrate how in Mexico, a middle-income country with near universal access to water and sanitation but where intestinal infections are the second main cause of child death and 11 percent of children under five suffer from acute diarrhea, the onset of the 2009 H1N1 influenza (swine flu) led to a large, robust and long-lasting *decline* in diarrhea cases of children. This is done with a difference-in-difference framework using a balanced panel of annual state-level data aggregated from hospital discharges related to diarrhea and the total number of laboratory *confirmed* cases of the swine flu in Mexico derived from Mexico's Ministry of Health (*Secretaria de Salud*).

Relying on administrative data –where trained medical professionals register their diagnoses– and several robustness checks, we rule out the possibility that our findings are driven by misdiagnosis of either H1N1 or diarrhea cases. Additional placebo tests and robustness checks further support our results. For example, we find no association between diarrhea-related cases *before* the H1N1 outbreak (2006–2008) and the number of confirmed swine flu cases observed in 2009. There is also no evidence of people avoiding hospitals altogether due to the H1N1 pandemic. Furthermore, the negative effect on diarrhea is also observed in morbidity cases beyond hospitalizations, as captured by Mexico's Annual Morbidity Statistics.

Unlike the small (and anticipated) nature of the seasonal flu, it quickly became clear that the new H1N1 strain was easily transmittable and that existing vaccines did not prevent contracting the swine flu. Thus, people experienced an environment where the new virus was affecting a large number of individuals, and could, in some cases, be fatal. This provides an important context to test theoretical models of health behavior where a decision to engage in preventive behavior is triggered only when the (contagious) disease crosses a high threshold (e.g., Philipson 2000). Consistent with such models, we find a null effect for the seasonal flu on diarrhea outcomes that contrasts with our negative and large findings from the H1N1.

Using Google searches originated in Mexico we identify an increase in the demand to learn about preventive behaviors. Specifically, we find that searches for the word “hand sanitizer” spiked during the peaks of the pandemic. Furthermore, we show that an

increase in the incidence of the H1N1 is associated with more searches for this preventive behavior. Other mechanisms, such as the role of government expenditure and health infrastructure, do not seem to play a major role.

Further incidence of the H1N1 after 2009 allows us to test whether such “reminders” continue to have an impact on health outcomes beyond 2009. Using an event study we show that the *contemporaneous* negative effect is observed in 2009 and 2010 but disappears by 2012. However, when testing for the persistence of the 2009 shock, we find that this effect dominates the contemporaneous impact suggesting long-lasting consequences of the larger shock. This is an important result because, as we will show later, the evidence on whether information campaigns have long-lasting effects is scant (e.g., Cairncross et al., 2005).

Taken together, our results provide empirical support to recent behavioral economics models where large health shocks alter the risk perceptions of individuals and affect the production of health outcomes. In that regard, our findings are consistent with previous studies that have shown, in the case of the United States, that smokers are more likely to quit when they experience more severe health shocks (Sloan et al., 2003; Margolis et al., 2014). It is also consistent with the findings from Philipson and Posner (1994), who document a rapid reduction in gonorrhea for the male homosexual community in San Francisco as a result of a change towards safer sex practices soon after the onset of the HIV pandemic.

The rest of the paper is divided into six additional sections. We start by briefly describing the H1N1 outbreak in Mexico in section two. Section three describes the data sources and our econometric model. The main results, including our robustness checks, are presented in section four. Section five describes the possible mechanisms while section six examines the persistence of the effects. Section seven summarizes our findings, discusses policy implications as well as the way our paper expands our understanding of the production of health outcomes and concludes.

2. Mexico and the 2009 swine flu pandemic

In March and early April 2009, Mexico experienced an outbreak of respiratory illnesses which was later confirmed to have been caused by the novel influenza A(H1N1) 2009 virus or *swine flu*.⁶ The H1N1 is a contagious virus transmitted via droplets from coughs and sneezes or by interacting with infected people. This influenza virus can survive on environmental surfaces such as kitchen counters and door knobs for up to eight hours. H1N1 shares many of the symptoms of the seasonal flu: fever, cough, aches. However, while it is rare to have gastrointestinal symptoms from the seasonal flu, some cases of the swine flu, around 13 percent, exhibited nausea, vomiting or diarrhea (SSA, 2011).

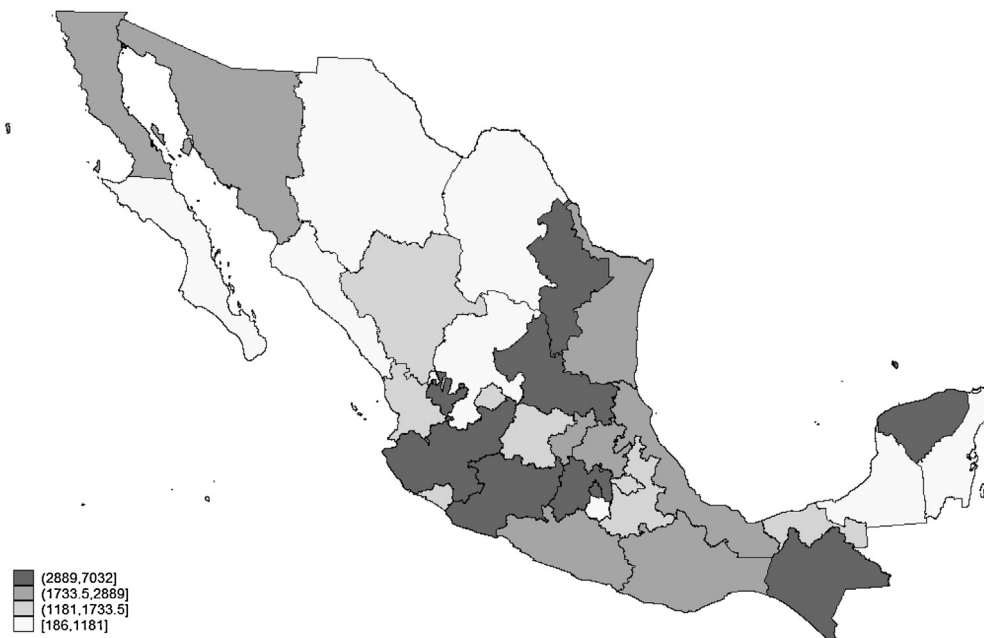
The World Health Organization (WHO) declared the 2009 H1N1 outbreak as the first flu pandemic in 41 years. As of June 2011, Mexico's Ministry of Health reported that there were more than 70,000 confirmed cases of swine flu in 2009, including more than one thousand deaths and around 2400 hospitalizations. Most of the confirmed H1N1 cases in Mexico involved a relatively younger cohort, aged 10–39, compared to the population typically affected by the seasonal influenza. The incidence of these cases was highest in May, June, and September of 2009 (Appendix Fig. 1 in Supplementary material). All states in Mexico were affected by the swine flu outbreak, but there was variation in the distribution of cases across states (Fig. 1, Panel A). This distribution does not coincide with the spatial pattern observed for diarrhea cases prior to 2009 (Panel B of Fig. 1).

⁴ Other examples include Kremer and Miguel (2007)'s finding that information had no effect on Kenyans' investing in deworming treatments, and Ashraf, Berry and Shapiro (2010)'s report that information had no effect on chlorine water purification in Zambia.

⁵ Other strategies include, but are not limited to, taxation, cash incentives and restrictions on use or purchase of preventive products. See Cawley and Ruhm (2011) for an extensive discussion of policy options and theoretical models related to risky behaviors in advanced economies. For developing countries, a growing literature explores the role of subsidies on the adoption of health products and behaviors. See Dupas (2011, 2014) for a review.

⁶ For an epidemiological description of the 2009 H1N1 in Mexico see Fajardo-Dolci et al. (2009) and Chowell et al. (2011).

PANEL A. LABORATORY CONFIRMED SWINE FLU CASES, 2009



PANEL B. DIARRHEA-RELATED HOSPITALIZATIONS, 2006-2008

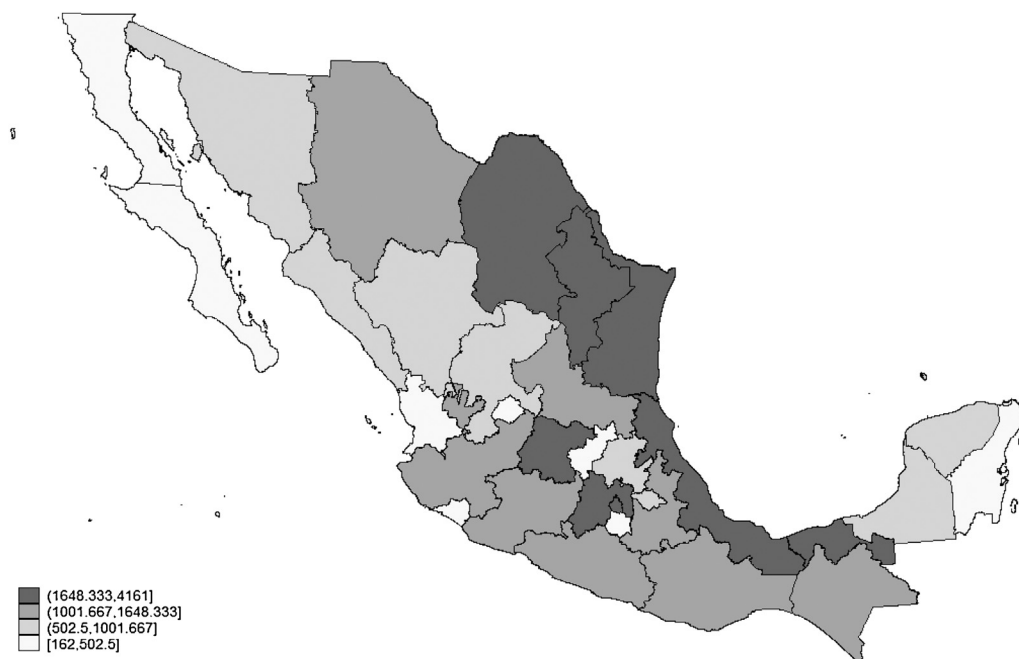


Fig. 1. Geographic Variation of Laboratory Confirmed H1N1 Cases and Diarrhea-related Hospitalizations in Mexico.

Panel A. Laboratory Confirmed Swine Flu Cases, 2009.

Panel B. Diarrhea-related Hospitalizations, 2006–2008.

Sources: Authors' analysis of hospital discharge data from Mexico's Ministry of Health (Secretaria de Salud).

The announcement of the first case of H1N1 on April 23, 2009, was followed by a series of other actions coordinated by the Mexican government, including the Ministry of Health, and other national and international organizations. These actions included enactment of the National Pandemic Preparedness and Response Plan which coordinated and implemented risk communication strategies to promote respiratory hygiene and to maintain the public informed about the transmission of influenza. TV and radio ads, a dedicated hot line, alert text messaging, and social media messaging were launched on April 25. The goal of the campaign was to educate the public about frequent and proper hand washing techniques, covering sneezes or coughs, using face masks and hand sanitizers, seeking care if ill, and discouraging self-medication. The Ministry of Health and the Office of the President coordinated with media outlets to provide daily updates on the number of confirmed cases, which was reflected on substantial coverage on the number of confirmed cases in each state as well as key messaging on how to prevent transmission.

On April 26, the World Bank lent \$25 million for immediate aid and \$180 million in long-term assistance to address the outbreak. The announcement of the World Bank aid was followed by the closure of schools nationwide on April 27. On April 30, the Mexican government declared that all “non-essential” activities be suspended and implemented social distancing measures that closed restaurants, entertainment venues, and cancelled large public gatherings nationwide. Throughout the development of the outbreak, the World Health Organization actively updated their assessment from “event of international concern” on April 24 to pandemic phase 4 (sustained community transmission) on April 27, to phase 5 (imminent pandemic underway) on April 29, and then to phase 6 (pandemic) on June 11.

Although the pandemic was still underway, activities began to return to normal in Mexico. By May 11, most schools had reopened nationwide. Parents and volunteers coordinated with school and health authorities to sanitize the schools with cleaning supplies paid for by the federal government before the schools reopened on May 11. In addition, parent-volunteers screened students in elementary schools to identify and send home students reporting or showing influenza-like symptoms. It is unclear how long the screeners were in place, but there are reports that screeners in schools were only present for a few days (SSA, 2009a). Additional collaboration at the state, local, and international level also occurred to disseminate information in the workplace, public transportation, and local communities, although the details are too varied for us to summarize here. There were other waves of cases in June and September, but they were reported to be under control. Appendix Table 1 in Supplementary material provides further details about measures taken by the Mexican government and other organizations in the first months following the first confirmed cases of H1N1. Thus, while the swine flu remains in Mexico today, none of the following years had the same level of intensity, awareness and possible “panic” as observed in 2009.

In the next section we describe our data and how we exploit the variation across time and space to identify the causal impact of an exogenous shock that induced changes in behavior and ultimately reduction in child diarrhea.

3. Data and methods

3.1. Data

We use several data sources for this paper, all but one, collected by Mexico’s Ministry of Health (*Secretaría de Salud*) to create a state-year balanced panel. First, we use hospital discharge data from all public hospitals. For the purpose of this study we use data for the

2006–2012 period and we aggregate the discharges at the year and state level to match the source of the time and spatial variation in the H1N1 data.⁷ Common to many developing countries, the public hospital system covers most of the population and in the case of Mexico, 85 percent of all hospital visits are covered by these hospitals.⁸ This large coverage strengthens the external validity of our findings.⁹

A key advantage of this dataset is that the coding for the primary diagnosis of the discharge follows the International Statistical Classification of Diseases and Related Health Problems 10th Revision or ICD-10, created by the World Health Organization (WHO, 2010), where the treating physician determines the diagnosis. Relying on the report of a trained professional represents a significant improvement in the literature as it helps reduce the recall bias and other measurement errors that plague self-reported data obtained from household surveys (Heady 2016) and improves the accuracy of the diagnosis. The coding included in the database comes from the actual diagnosis regardless of the initial reason that led the patient to the hospital.¹⁰ Furthermore, the use of hospital discharge data implies that we are focusing on the extreme and treated cases of diarrhea (i.e., those severe enough that resulted in a hospital visit and even death) as opposed to those cases that were either treated at local health centers, at home or went untreated.

Following Mexico’s Ministry of Health’s definition of “acute infectious diarrhea” we consider cases where the primary diagnosis was an intestinal infection as classified by ICD-10 codes A00 through A09X (SSA, 2012). The details of the codes are presented in Appendix Table 2 in Supplementary material. In Mexico, diarrheal cases in children under five represent 51 percent of all hospital discharges where the primary diagnosis was diarrhea.¹¹ For this reason and following the literature of early childhood development we restrict our analysis mainly to this age group.¹²

The hospital discharge data are complemented with morbidity information collected in the *Anuarios de Morbilidad*¹³ (Annual Morbidity Statistics). The *Anuario* is a yearly report produced by the Mexican Health System that collects information from all the public and private health centers nationwide to create an Epidemiological Surveillance Bulletin for the National System of Epidemiological Surveillance or *SINAVE*, similar to the CDC’s National Notifiable Dis-

⁷ Data covering some public hospitals are available from 2002. Data for all public hospitals are available beginning 2004, but we do not incorporate it into this analysis because the age variable was not consistently coded for that year. For 2005, we do not have information of the limited rollout of the rotavirus vaccination campaign and therefore restrict the sample to 2006 onwards when the rotavirus program was nationally implemented.

⁸ This dataset does not record month of admission. This variable is only included in a dataset that, unfortunately, has a heavily restricted coverage (<50% of the national discharges) and does not represent a random sample of all discharges. These limitations prevent us from using the month-recording dataset in our main analysis.

⁹ Mexico’s Ministry of Health reports that in 2009 there were 91.6 million users of the public hospital system. However, the report does not indicate whether the reported 91.6 million users included repeat users. (Sistema Nacional de Información en Salud (SINAIS). *Población usuaria por entidad federativa según institución*, 2009. Boletín de Información Estadística, Vol. III, Servicios Otorgados y Programas Sustantivos, Numero 29, Año 2009. <http://www.sinais.salud.gob.mx/publicaciones/index.html>, last accessed November 24, 2013.

¹⁰ The primary diagnosis is determined based on the condition that was investigated and treated during the hospitalization. It is defined as, “The diagnosed condition at the end of the event that led to the primary cause of treatment for the patient. . . if there is more than one (condition), the one that is considered to be responsible for the most use of resources must be selected. If no diagnosis is made, the primary diagnosis is the main symptom, abnormal finding or problem” (SSA, 2010a, p.78).

¹¹ There were 5.8 million hospital discharges in Mexico in 2011 with a rate of 456.3 discharges per 10,000 population and 129,000 cases were related to diarrhea.

¹² Older children (5–14) represent 15 percent of all the hospital discharges diagnosed as diarrhea while people 45 and older constitute 20 percent of the cases.

¹³ Available at <http://www.epidemiologia.salud.gob.mx/anuario/html/anuarios.html>

eases Surveillance System in the United States. The *Anuarios de Morbilidad* concentrates on the leading causes of morbidity rather than collecting all possible diseases. It includes ambulatory and physician office visits. This facilitates a weekly report of the incidence of selected diseases, where acute respiratory infections as well as gastrointestinal diseases have been consistently covered in the data throughout the period of analysis. As in the case of the hospital discharge data, diagnoses recorded in the *Anuarios de Morbilidad* follow the ICD-10 classification and have been determined by a medical professional. In addition, there is a quality assurance process that includes a multi-layer system of checks until the data are released to the public months after the end of the calendar year. This dataset complements our hospitalization records and is available at the state level and not at the individual case level.

The third data source also comes from *SINAVE* and provides us with the swine flu cases –coded as J09–at the state level *only*, and yearly from 2009 onwards.¹⁴ A key advantage of this source is the quality of the report. The swine flu cases included in the dataset have been *confirmed* by a laboratory as true cases of the H1N1 (SSA, 2010b). In an effort to improve and standardize influenza surveillance, the Ministry of Health required all Mexican medical institutions to confirm suspected cases of the H1N1 with laboratory tests –a practice that continues to this day (SSA, 2010b, 2013, 2014). This heavily limits the possibility of misclassification with other diseases that could share symptoms with the swine flu.¹⁵ Additional data on health expenditures by the government (state and Federal), distribution of oral rehydration salts, distribution of vaccines, and hospital infrastructure as measured by the number of hospital beds come from Mexico’s Ministry of Health SINAI (National System of Health Information) data system.¹⁶

We utilized two other data sources. Child mortality due to diarrhea is obtained from Mexico’s Vital Statistics. This dataset has 100 percent coverage and includes deaths that occur at home and in hospitals.¹⁷ Also, we use Google Trends data as they provide an index that captures the popularity of a given Internet search across time and states. There is a growing number of papers using data from Google searches (available as *Google Trends*: <http://www.google.com/trends/>) to uncover economic issues. For example, these data have been used to predict economic indicators in the United States and Germany (Choi and Varian, 2012; Askitis and Zimmermann, 2009; D’Amuri and Marcucci, 2010) as well as discrimination and voting behavior (Stephens-Davidowitz, 2014).¹⁸ In our case, we are interested in searches of the Spanish word for hand sanitizers: “gel” or “gel antibacterial.” We downloaded the information in pairs of states keeping constant the state with the highest value of searches between 2008 and 2009 because Google Trends only releases it as index. In that way, our data provide the

¹⁴ Multiple symptoms can be associated with the swine flu. The top two symptoms associated with potential cases of the swine flu were cough (90 percent) and fever (86 percent), with diarrhea, nausea or vomiting being present in 13 percent of the cases (SSA, 2011).

¹⁵ An alternative to laboratory-confirmed cases could be the use of the actual number of people infected with H1N1. However, this number is unknown, as infections do not always create influenza-like symptoms and different approaches are used to compute estimates for the aggregate number of infections (Shrestha et al., 2011).

¹⁶ We also explored data on news coverage from a targeted search for H1N1-related articles during the period 2006–2012 in LexisNexis that included 14 major newspapers with national coverage in Mexico. However, there is no spatial variation in this variable and cannot be used in the analysis.

¹⁷ Mathers et al. (2005) classify Mexico’s mortality records as of the highest quality globally, with 100% coverage, extensive usage of ICD codes and with only 5% ill-defined codes. The United States has the same numbers except that it has 7% of ill-defined codes. Germany’s record for this measure is 14%.

¹⁸ Google even has a site dedicated to predict the incidence of the seasonal flu based on the results from a paper published in *Nature* (Ginsberg et al., 2009).

same base, where the highest (lowest) volume is set to 100 (zero).¹⁹ Note that the index is a measure of “relative popularity” and so it already takes into account the size of the search volume in each state and period.

Table 1 presents summary statistics of the key variables used in our analysis for periods 2006–2008, 2009, and 2010–2012. The last column of Table 1 shows the *p*-values of the difference in means between the pre-2009 and post-2009 periods. Given that H1N1 did not exist prior to 2009, the total number of *confirmed* cases of H1N1 is only available from 2009 onwards. Diarrhea-related hospitalizations for children under the age of 5 were lower in the post-2009, compared to the pre-2009 period, and the difference is statistically significant (*p*-value = 0.000). On the other hand, federal expenditures in health were higher in post-2009 than pre-2008 (*p*-value = 0.020). Except for these two variables, the test of difference in means suggests there is no difference between the pre-2009 and post-2009 periods as captured by most key variables.

3.2. Methods

We exploit the temporal (the onset of the swine flu in 2009) and cross-sectional variation (by state) of the swine flu to examine its effect on diarrhea cases, that is, diseases that may be prevented with improved hygiene behavior that followed the onset of the H1N1 pandemic in Mexico. Using a balanced panel at the state and year-level, our difference-in-difference identification strategy is formally presented in Eq. (1),

$$y_{st} = \alpha + \beta \text{H1N1}_{st} + \tau_t + \theta_s + e_{st}, \quad (1)$$

where y_{st} is the number of hospital discharges with a primary diagnosis of intestinal infections (henceforth referred to as diarrhea) for state s in year t . Variable H1N1_{st} represents the cross-sectional and temporal variation in the number of laboratory-confirmed swine flu cases reported in each of the states and year (with values equal to zero before 2009). We also investigate other treatment and baseline periods, which are discussed in Section 4.3. We use H1N1 counts rather than rates because we believe that part of the mechanism through which individuals’ perceptions changed was rooted in the perceived magnitude of the problem as reported on news media channels. The news media reported the total number of cases that had been confirmed at the national level as well as the states where the highest number of cases had been confirmed.²⁰ Thus, β is our parameter of interest as it captures the difference-in-difference impact. Robust standard errors clustered at 32 states with a correction with a correction for small clusters are used and are complemented with *p*-values computed using a wild bootstrap method (Cameron et al., 2008).

Eq. (1) includes controls for year and state fixed effects (τ_t and θ_s , respectively). The year fixed effects allow us to control for nationwide trends in diarrheal diseases while the state fixed effects account for time-invariant unobserved characteristics during the period of analysis at the state level (e.g., culture, geography, institutional settings).

In our main specification, we compare the changes in diarrhea cases between 2008 and 2009 as we expect several state characteristics, including health infrastructure (e.g., stocks of hospitals and clinics), to remain constant over such a short period, thereby reducing the possibility of a bias in the parameter of interest. Thus, if the H1N1 pandemic induced changes in hygiene behavior, we would expect to observe a larger *decline* in the incidence of diarrheal dis-

¹⁹ See <https://support.google.com/trends/answer/4365533?hl=en> for details. Last accessed on May 4, 2016.

²⁰ See for example, <http://www.eluniversal.com.mx/notas/629954.html>, and <http://www.eluniversal.com.mx/notas/636158.html>, accessed November 4, 2013.

Table 1
Descriptive Statistics: 2006–2012.

Variable Description	(1) 2006–2008: Mean	(2) 2009: Mean	(3) 2010–2012: Mean	(4) 2006–2008 vs 2010–2012: <i>p</i> -value ^a
Diarrhea-related Hospitalizations ^b : Children Ages 0–4	1,370.63	938.56	824.93	0.000
Diarrhea Cases (Morbidity) ^b : Children Ages 0–4	53,168.35	47,692.00	47,582.96	0.257
Confirmed Cases of H1N1: All Ages	0	2,186.00	78.91	0.000
Hospitalizations: All Ages	153,126.70	163,811.00	170,885.30	0.314
Federal Expenditures in Health (Millions of Mexican Pesos)	4,922.19	4,876.20	5,394.33	0.020
State Expenditures in Health (Millions of Mexican Pesos)	774.68	981.86	931.50	0.450
Vaccine Doses ^c (1000s)	2,790.70	3,329.32	3,394.27	0.132
Oral Rehydration Salts (ORS) ^d (1000s)	113.46	88.29	92.19	0.106
Number of Hospital Beds	1,137.84	1,130.00	1,129.13	0.962
Observations	96	32	96	192

Sources: Mexico's Ministry of Health (Secretaria de Salud); SINAIS (National System of Health Information).

Notes: Each year of analysis includes Mexico's 31 states and its Federal District (Mexico City).

^a The *p*-value is for the difference in means between the periods 2006–2008 and 2010–2012.

^b Includes the mean number of hospital dischargers (or morbidity cases) where the primary diagnosis was International Classification of Diseases (ICD-10) code A00-A09X (Intestinal Infections) for children under the age of five.

^c Vaccine Doses denotes the mean number of vaccinations that were administered in a state during the period of analysis, including vaccinations against the rotavirus.

^d ORS denotes the average number of oral rehydration salt packets that were distributed in a state during the period of analysis.

eases in states where the swine flu was *more* prevalent. In other words, we would expect β to be negative and statistically significant. In the next section, we show the results of estimating Eq. (1) with the data described above.

4. Impact of the swine flu pandemic

4.1. Main findings

Table 2 presents the results from running the specification described in Eq. (1) for 2009 and 2008, with state and year fixed effects. As shown in Panel A, column 1, our estimate for effect of the 2009 H1N1 on diarrhea cases for children under five is negative, -0.105 , and statistically significant at the five percent level, marginally, using the wild-bootstrap *p*-values (0.060). That is, there were *fewer* hospital discharges related to diarrhea in states with *more* swine flu cases, even after controlling for time and state fixed-effects. This coefficient implies that for every 1000 cases of the swine flu, there were 105 *fewer* cases of diarrhea in children under five. Given the average number of diarrhea-related hospitalizations for this group (1117 in the period 2008–2009), the estimated association indicates that for every 1000 cases of the swine flu we observe a 9.4 percent decline in diarrhea-related hospitalizations ($-0.105 \times 1000 / 1117$). That is, 3404 cases of H1N1 (or 4.9 percent of all confirmed cases) would have the same effect in the reduction of diarrhea (32 percent) as the estimated average effect from the costly interventions reviewed by Ejemot-Nwadiaro et al. (2008).

This finding is reinforced when using the morbidity data (Panel B) that covers cases recorded in all public and private health centers, except for hospital inpatients. We find that 1000 cases of the H1N1 are linked to a 3.5 percent reduction in diarrhea cases among young children (*p*-value = 0.051). This impact is smaller than the 9.4 percent found in the inpatient setting, suggesting that the effect is more pronounced among severe cases, that is, those that required hospitalization.

4.2. Possible misclassification of diseases

In this section we examine the possibility that the documented reductions in diarrhea cases were purely “mechanical” and driven by a misclassification of diagnoses created by the onset of the swine flu. For example, with the arrival of the H1N1, cases that should have been identified as diarrhea (belonging to ICD codes A00-A09X) could have been incorrectly classified as swine flu. After all, up to 13 percent of the diarrhea swine flu cases exhibited vomit, nausea

or diarrhea as an additional symptom. We argue that this misclassification is an unlikely event for the following reasons. First, as explained in the data section above, the H1N1 cases used in our study were *confirmed* cases using laboratory tests. So even if some of them included a diarrhea symptom, these cases were coded as J09 in our data because a strain of the novel type of influenza was found in these patients. Second, the recorded disease is made by a trained medical professional. So if parents suspect their children have H1N1, when the actually have diarrhea, what is recorded is the actual assessment of the physician and not what the patient (or his parents) suspected.²¹ Third, we expect medical professionals to be less likely to misdiagnose a diarrhea case not only because of their medical training but because Mexico has identified intestinal infections as a public health issue based on the magnitude and prevalence of the disease (with at least 11% of children under five being affected by this problem each year). These professionals are also more likely to be aware of the population at risk for different diseases. As shown in Fig. 2, which presents the age distribution of these two diseases for hospitalizations,²² the H1N1 affected disproportionately school-going children and adults while diarrhea affects primarily children under 5. This difference further reduces the possibility of misclassification.

Fourth, even if one assumes that doctors might not be fully aware of these epidemiological differences but rather have a flat prior with respect to the risk by age groups, then we should expect the misclassification to take place at all ages. However, when we run our main specification for other age groups and not just for children under five, we do not find evidence suggesting there is a mechanical misclassification of diarrhea to H1N1 (Table 3). The parameter for the H1N1 is negative and statistically significant for those under five (column 2). However, it is positive, small and not statistically different from zero for all other age groups (columns 1, 3–5), including older patients who are the second most at-risk age group of diarrhea (as shown in Fig. 2, Panel B). This pattern –negative effect for children under five and positive but close to zero for all other groups– is found using the hospitalization (Panel A) data as well as the overall morbidity data (Panel B).

Moreover, we explore other outcomes that could be affected by better hygiene practices. In Table 4 we include cases of conjunc-

²¹ It is worth noticing that the official guidelines sent by the Mexican government to parents and schools rarely include diarrhea as one of the key symptoms to identify a possible H1N1 case. See SSA (2009b) and SSA (2010c) for examples.

²² See Appendix Fig. 2 in Supplementary material for morbidity cases.

Table 2
Prevalence of Intestinal Infections for Children under Five Using Alternative Baseline Periods.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Period of Analysis	2009 vs 2008	2009 vs 2007	2009 vs 2006	2006–2009	2006–2009	Pre-2009	Pre-2009
Panel A. The Dependent Variable Captures Diarrhea-related Hospitalizations ^a							
H1N1 ^b	-0.105 (0.040)	-0.218 (0.065)	-0.105 (0.057)	-0.143 (0.044)	-0.143 (0.062)	0.000 (0.023)	
p-value ^c	0.060	0.140	0.202	0.089	0.105	0.998	
R ²	0.588	0.602	0.431	0.406	0.681	0.144	
Mean (\bar{Y})	1,117	1,221	1,126	1,263	1,263	1,371	
Obs.	64	64	64	128	128	128	
State Trends ^d	No	No	No	No	Yes	No	
Panel B. The Dependent Variable Captures Diarrhea Cases (Morbidity) ^e							
H1N1 ^b	-1.737 (0.786)	-1.402 (0.897)	-1.480 (0.933)	-1.448 (0.540)	-1.540 (0.663)	0.061 (0.210)	
Seasonal Flu ^f							0.003 (0.003)
p-value ^c	0.051	0.295	0.101	0.058	0.000	0.788	0.121
R ²	0.501	0.442	0.476	0.287	0.289	0.022	0.613
Mean (\bar{Y})	49,977	50,502	50,811	51,799	51,799	53,205	1,371
Obs.	64	64	64	128	128	128	96
State Trends ^d	No	No	No	No	Yes	No	No

Notes: Columns (1), (2), and (3) are pairwise comparisons where the control period is 2008, 2007, and 2006, respectively, and the treatment period is 2009. For columns (4) and (5) the control period is 2006–2008 and the treatment period is 2009. For column (7), the treatment period is 2008, and the control period is 2006–2007. All regressions include time and state fixed effects. Mean (\bar{Y}) denotes the mean of the dependent variable for each specification and for the period of analysis.

^a The dependent variable is the annual number of hospital discharges where the primary diagnosis was International Classification of Diseases (ICD-10) code A00–A09X (Intestinal Infections) for children under the age of five.

^b H1N1 is equal to the number of confirmed H1N1 cases in a given state in 2009 and zero otherwise.

^c p-value denotes the p-value of wild bootstrapped standard errors for a given specification to correct for small number (32) of clusters.

^d State Trends denote state-specific linear trends.

^e The dependent variable is the number of diarrhea cases (morbidity).

^f The treatment is denoted by “Seasonal Flu” which captures the number of seasonal flu cases in a given state and year.

Table 3
Impact of H1N1 Prevalence on Intestinal Infections by Age Groups: 2008 vs 2009.

Age Group:	(1)	(2)	(3)	(4)	(5)
	All	0–4	5–14	15–44	45+
Panel A. The Dependent Variable Captures Diarrhea-related Hospitalizations ^a					
H1N1 ^b	-0.064 (0.053)	-0.105 (0.040)	0.026 (0.010)	0.000 (0.009)	0.015 (0.007)
p-value ^c	0.141	0.060	0.597	0.994	0.266
R ²	0.442	0.588	0.188	0.002	0.115
Mean (\bar{Y})	2,270	1,117	359	84	444
Observations	64	64	64	64	64
Panel B. The Dependent Variable Captures Diarrhea Cases (Morbidity) ^d					
H1N1 ^b	1.253 (2.011)	-1.737 (0.786)	0.847 (0.456)	1.395 (0.741)	0.745 (0.495)
p-value ^c	0.565	0.051	0.246	0.220	0.256
R ²	0.026	0.501	0.345	0.308	0.182
Mean (\bar{Y})	167,612	49,977	32,005	51,908	33,605
Observations	64	64	64	64	64

Notes: All regressions include time and state fixed effects. The period of analysis is 2008–2009. Mean (\bar{Y}) denotes the mean of the dependent variable for each specification.

^a The dependent variable is the annual number of hospital discharges where the primary diagnosis was the International Classification of Diseases (ICD-10) codes A00–A09X for all males and females in respective age group.

^b H1N1 is equal to the number of H1N1 cases in a given state in 2009 and zero in 2008.

^c The p-value denotes the p-value of wild bootstrapped standard errors for each specification to correct for small number (32) of clusters.

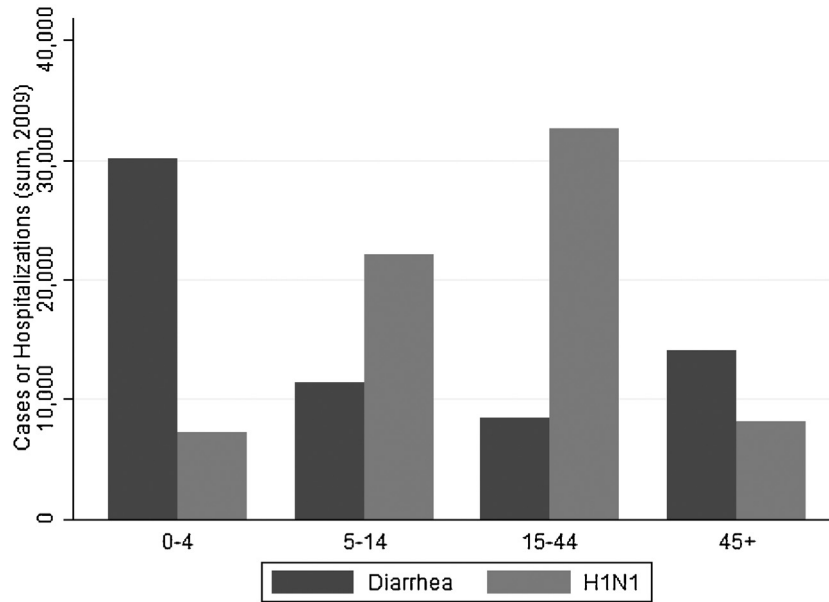
^d For Panel B the outcome is number of diarrhea cases (morbidity) for all males and females in respective age group.

tivitis (ICD-10 codes B30 and H10) for children under 5 (column 2). This outcome comes from the morbidity dataset obtained from the *Anuarios de Morbilidad*. We find a negative association between H1N1 and conjunctivitis cases. However, conjunctivitis affects only a fraction of children under five compared to diarrhea. In 2008, for instance, there were 1.5 million cases of diarrhea nationwide but only 89,103 cases of conjunctivitis. This could explain the lack of statistical significance for this estimate. When we add hepatitis A (ICD-10 code B15, also from the *Anuarios de Morbilidad*) and conjunctivitis together as a new outcome we continue to observe a negative association with H1N1, alas unable to reject the null

hypothesis (results available upon request). Again, this could be explained by the few cases of hepatitis A among this age group (only 4348 in 2008) relative to the diarrhea cases. We think this evidence, although not as strong as desired, adds to the support that the negative, robust and statistically significant effect of H1N1 on diarrhea is less likely to come from a mechanical classification problem.

Finally, we take advantage of the fact that diarrhea cases are classified in different ICD codes depending on the cause or disease etiology, where for most cases the cause of diarrhea is not known. If during the H1N1 outbreak doctors misclassified diarrhea

Panel A. Confirmed Cases of H1N1 and Diarrhea-related Hospitalizations, 2009



Panel B. Diarrhea-related Hospitalizations, 2008-2009

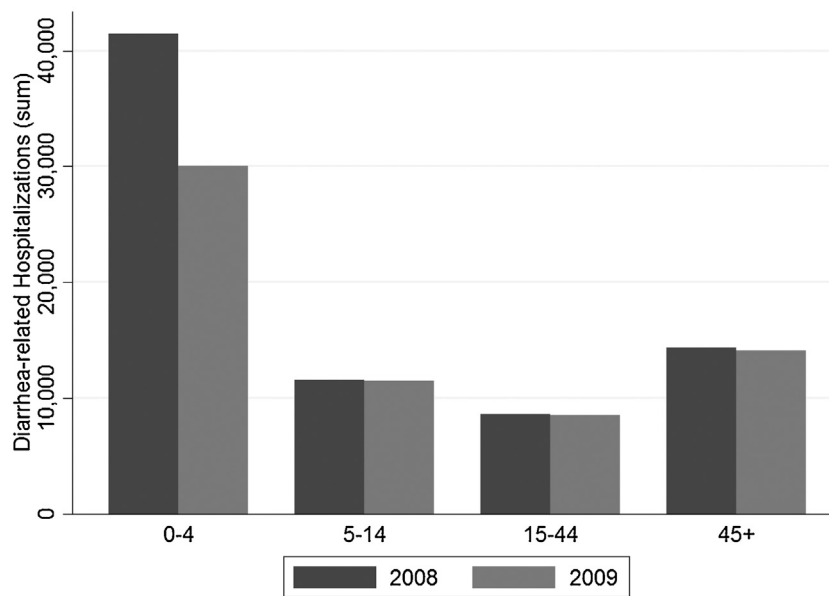


Fig. 2. Confirmed Cases of H1N1 and Diarrhea-related Hospitalizations: by Age Groups.
 Panel A. Confirmed Cases of H1N1 and Diarrhea-related Hospitalizations, 2009.
 Panel B. Diarrhea-related Hospitalizations, 2008–2009.
 Source: Authors' analysis of data from Mexico's Ministry of Health (*Secretaria de Salud*).

cases, these cases are more likely to come from those where the cause is unknown (ICD-10 code A09X) and much less so, if at all, from those where the cause is known (ICD-10 codes A00-A08) (see Appendix Table 2 in Supplementary material for details about specific ICD-10 codes). In Table 4 we test for this hypothesis by using the ratio between *known* cases of diarrhea and the *unknown* sources as our outcome variable. Misclassification implies that more cases of H1N1 will be *positively* associated with this ratio: the denominator (the unknown sources) decreases but not the numerator. Our estimates strongly reject this prediction of misclassification.

We find no association between the ratio and the H1N1 (Table 4, column 1). Specifically, our point estimate using hospitalizations is 0.0001 (bootstrapped p -value = 0.853) and a similarly small and not statistically different from zero estimate when using the morbidity dataset (coefficient = 0.0001, p -value = 0.136).²³ Taken together,

²³ When using hospitalizations (for whom we have all the diarrhea categories) we continue to observe a decline among the known causes of diarrhea, clearly contradicting the misclassification threat.

Table 4
Robustness Checks: Impact of H1N1 on Other Outcomes, 2008 vs 2009.

Panel A. Impact of H1N1 on Select Measures of Hospitalizations ^a				
	(1) Known/Unknown Causes of Diarrhea ^b	(2) Hospitalizations due to Injuries ^c	(3) Hip-related Procedures ^d	(4) Total Hospital Discharges: excl. H1N1
H1N1 ^e	0.0004 (0.001)	0.005 (0.007)	0.089 (0.033)	0.123 (0.146)
p-value ^f	0.830	0.782	0.903	0.898
R ²	0.026	0.033	0.264	0.037
Mean (\bar{Y})	14.23	831	2,055	15,840
Obs.	64	64	64	64
Age Group	0–4	0–4	All	0–4
Panel B. Impact of H1N1 on Select Morbidity and Mortality Measures ^g				
	(1) Known/Unknown Causes of Diarrhea Cases ^b	(2) Conjunctivitis ^h	(3) Mortality (Deaths)	
H1N1 ^e	0.0004 (0.0003)	–0.042 (0.039)	0.0003 (0.002)	
p-value ^f	0.136	0.334	0.925	
R ²	0.137	0.054	0.324	
Mean (\bar{Y})	11.5	2742	34	
Obs.	64	64	64	
Age Group	0–4	0–4	0–4	

Notes: All regressions include time and state fixed effects; period of analysis is 2008–2009. Mean (\bar{Y}) denotes the mean of the dependent variable for each specification and for the period of analysis.

^a The dependent variable is annual hospital discharges as specified in each column.

^b Known causes include International Classification of Diseases (ICD-10) A00–A08; Unknown causes include ICD-10 code A09X.

^c Injuries include ICD-10 codes S00–S798.

^d Hip-related procedures include codes that capture fracture of femur (S72), arthrosis of hip (M16), complications of surgical and medical care (T80–T85), presence of orthopedic joint implants (Z96.6), fracture of bone following insertion of orthopedic implant (M96.6), and fitting and adjustment of orthopedic device (Z46.7).

^e H1N1 denotes the number of confirmed H1N1 cases in a given state during the treatment period (2009), and zero otherwise (2008).

^f p-value denotes the p-value of wild bootstrapped standard error to correct for small number (32) of clusters.

^g The dependent variable is the annual number of diarrhea cases or deaths due to diarrhea as specified in each column.

^h Conjunctivitis includes ICD-10 codes B30 and H10.

all these results indicate that our findings are not driven by some misclassification of the diagnosis.²⁴

4.3. Alternative base periods and pre-existing trends

A key advantage of comparing diarrhea cases between 2009 and 2008 is their proximity in time. In such a short period, the inclusion of state fixed effects serves as a more credible assumption because unobservables, such as culture or geography and maybe even institutions, are less likely to vary compared to the use of longer periods. Nonetheless, it could be the case (however unlikely) that some of the unobserved characteristics specific to the 2008 cross-sectional distribution of the diarrhea cases could “predict” the spread of the 2009 swine flu and therefore bias our estimates. With that in mind, we explore whether redefining or expanding the base period alters our findings.

We consider two alternative specifications using the hospitalization and morbidity outcomes. First, following Eq. (1) we estimate two pairwise comparisons separately: 2009 vs. 2007 (column 2 of Table 2) and 2009 vs. 2006 (column 3 of Table 2). The second specification discards the pairwise comparison and expands the sample

²⁴ We also explored the possibility that, before 2009, the new strain of the H1N1 virus might have been a latent disease and those cases were incorrectly labeled as diarrhea, because the new virus has not been identified yet. Based on the number of H1N1 cases in 2009 for children under five (7238) and that 13% of cases, that at most, could include a diarrhea-like symptom, we estimated that the highest number of cases incorrectly labeled as diarrhea for 2008 cannot exceed 2.3 percent of the hospitalizations and 0.06% of the morbidity data. Re-running our equation with those reductions applied to 2008 do not change our results (available upon request). We thank an anonymous referee for this point.

to include all years 2006–2009 (columns 4 and 5 of Table 2). The inclusion of more years permits us to add state-specific trends that were not possible in the pairwise comparison. The results of these new specifications indicate that our findings are not sensitive to these changes. Specifically, defining 2007 or 2006 as the base year does not qualitatively alter our conclusion. We continue to find a negative association (but with lower precision) and these parameters are not statistically different from the estimates using the original base year. Furthermore, expanding the data to include 2006 through 2009 we conclude that controlling for state trends (column 5) or not (column 4) provides robust findings: areas with a higher incidence of H1N1 see a larger decline in the number of diarrhea cases (with significant levels of 10 percent for hospitalizations and even lower for morbidity). All these findings hold when using the hospitalization data (Panel A) or the morbidity (Panel B). Thus, it is unlikely that our results are capturing pre-existing trends, as we continue to find a negative association between H1N1 and diarrhea cases after we control for time varying unobserved characteristics by state.

We further explore the issue of possible, though unlikely, pre-existing trends. In Fig. 3 Panel A we first show that states with a higher incidence of the 2009 swine flu had a larger decline in the number of diarrheal cases relative to the years preceding the outbreak. We then examine the impact of the prevalence of the H1N1 pandemic on diarrhea cases for the periods preceding 2009. Fig. 3, Panel B, illustrates that there is no association between diarrhea-related cases between 2008 and 2007 (before the H1N1 outbreak) and the number of confirmed swine flu cases observed in 2009.

The regression analog to this figure is shown in Table 2, column 6. There we run the same specification as in Eq. (1) for the diarrhea outcomes in 2006–2007 and 2007–2008 but *incorrectly* assign the

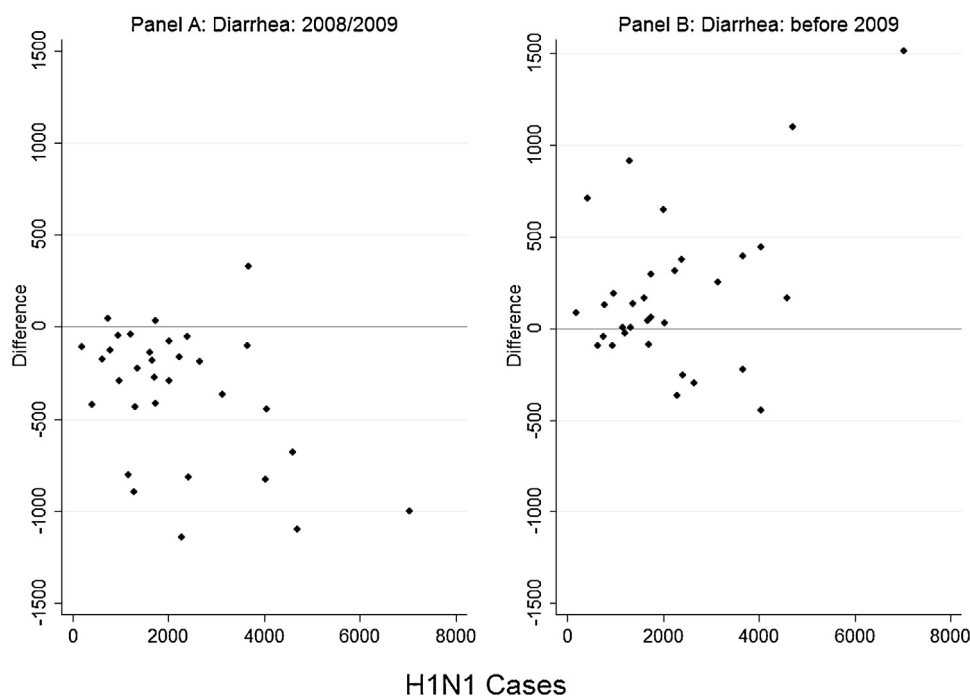


Fig. 3. Changes in Hospitalizations for Children under Five Years of Age.

Notes: Mexico has 31 states and the Federal District (Mexico City), each of which is represented by a point on Panel A and Panel B. In Panel A, each point represents the difference in the average number of cases of diarrhea between 2008 and 2009 in each state. In Panel B, each point represents the difference between the average number of cases of diarrhea in 2006–2007 and the average number of confirmed H1N1 cases in 2009 in each Mexican state.

Sources: Authors' analysis of hospital discharge and H1N1 laboratory confirmed data from Mexico's Ministry of Health (*Secretaria de Salud*).

2009 H1N1 distribution to these previous periods of time (for hospitalizations and morbidity, Panels A and B, respectively). As before, we should find no effect of the 2009 H1N1. Otherwise, this would be evidence in favor of unobserved variables predicting the 2009 cross-sectional distribution of the swine flu. In each case, hospitalizations and morbidity data, the estimates for this falsification test indicate true zero effects. These zero estimates and the lack of statistically significant effects provide a much stronger validation of our identification strategy and it is consistent with the visual evidence provided in Fig. 3 Panel B as well as the two maps presented before (Fig. 1).

4.4. Additional robustness checks

For our next set of falsification tests, we continue to compare data between 2008 and 2009 but alter the outcomes examined. In particular we use: injuries caused by external factors²⁵ (e.g. traffic accidents, ICD-10 codes S00–T98), hip-related procedures (ICD-10 codes S72, M16, T80–T85, Z96.6, M96.6, and Z46.7), all hospital discharges (all ICD-10 codes excluding H1N1 cases) as well as mortality due to gastrointestinal problems (see Appendix Table 2 in Supplementary material for more details about the ICD-10 codes for these diseases).

First, as a way to start introducing some of the possible mechanisms behind the observed effect of the swine flu (i.e., hand washing) we show that the H1N1 does not affect discharges *unrelated* to hand washing. Specifically, hospital discharges due to injuries serve as a valid placebo effect and we would expect to find statistically insignificant effects when we estimate Eq. (1) using injuries as an outcome. This is precisely what we observe in col-

umn 3 of Table 4. The effects are again true zeroes: very small effects with smaller standard errors. For example, the point estimate is 0.005 (SE = 0.007, bootstrapped p -value = 0.782), which is twenty times smaller than the corresponding estimate for diarrhea (in absolute value).

Second, we want to rule out the possibility that we are attributing our main findings to changes in healthcare-seeking behavior, namely, that there were fewer people going to the hospital in areas with higher prevalence of H1N1 in order to avoid contact with sick individuals. We provided evidence against this possibility earlier as we showed that the effects are also observed among morbidity cases, beyond hospitalizations. We explore this using hospital discharges associated with hip-related procedures for all age groups, and hospital discharges (excluding H1N1) for children under five. Hip-related procedures try to capture hospital visits that could be delayed. If these procedures were negatively related to the H1N1, we would find evidence that adults were avoiding hospitals. In column 3 of Table 4 we identify a null result. Similarly, if we observe a statistically significant decline in all types of hospitalizations for children, it would also suggest that parents were not taking their children hospitals. A null result for this outcome is presented in column 4 of Table 4. If anything, in both cases we find a (very small) positive parameter that is not statistically significant. Thus, we can rule out the possibility that our findings come from people avoiding hospitals during the swine flu pandemic.²⁶ In column 3 of Table 4 Panel B, we show the results of the analysis where mortality due to diarrhea is the outcome measure. The estimated coefficient is 0.0003 and is not statistically significant, implying that there is no change in overall child mortality due to diarrhea in areas with more cases of the swine flu. This is important as we can rule out deaths

²⁵ Injuries includes trauma to body, burns, poisoning due to external factors such as falls, traffic accidents, self-inflicted injuries, exposure to inanimate falling, thrown or projected objects, and aggressions.

²⁶ Bennett et al. (2015a) show that during the SARS epidemic in Taiwan outpatient visits fell by more than 30 percent in the course of a few weeks and that this was in response to public information as well as the behavior and opinions of peers.

from diarrhea happening at home, rather than at hospitals, for areas of high H1N1 prevalence.²⁷

5. Possible mechanisms

How did the swine flu reduce diarrhea cases? In the previous section we have already suggested one possible explanation: the swine flu created a change in hygiene practices that led to more hand washing with soap (or use of antibacterial gels) and this led to fewer diarrhea cases requiring hospitalization, as well as fewer morbidity cases. In this section we provide further evidence in favor of this mechanism and rule out other possible pathways.²⁸

5.1. Government expenses, vaccinations, hospital capacity, and search for information

In this subsection, we examine several avenues that could explain the mechanisms underlying our findings. First, we consider “business-as-usual” variables. These include, state as well as federal health expenditures, the distribution of oral rehydration salts, the total number of vaccines administered and changes in health infrastructure measured by number of hospital beds. In Table 5 we display the results of using our difference-in-difference approach described in Eq. (1) when these variables are considered as outcomes, after controlling for time and state fixed effects.

In columns 1 and 2, we show that the estimated coefficients for state and federal expenditures, respectively, are positive, very small and clearly not statistically significant based on the bootstrapped *p*-value. Similar null results are found for oral rehydration salts, vaccines and hospital beds (columns 3–5). The spread of the H1N1 is not related to these variables ruling them out as possible mechanisms to explain the improvements in health outcomes.

We now present evidence in favor of a pathway where the 2009 H1N1 pandemic changed health behaviors in Mexico. We start by exploring production and consumption patterns of hygiene products. Mexican manufacturing data indicate that between 2008 and 2009, there was a 6.4 percentage point increase in production of soaps, cleaners and cosmetics; compared to a 2.3 percentage point increase from 2003 to 2007.²⁹ In addition to the changes in production of soaps there is other evidence that suggests changes in hand washing behavior might have occurred during the pandemic. A survey conducted in Mexico City and two states with varying prevalence of the swine flu showed that the top three mitigation efforts adopted to protect against the H1N1 virus included frequent washing of hands with soap, use of a mask, and hand sanitizer (Aburto et al., 2010).³⁰ We reproduce these findings in Appendix Table 5 in Supplementary material. This table also shows that people in states

²⁷ We also conducted additional tests to examine alternative functional specifications. These analyses suggest that the linear specification with counts appears to be the preferred specification for our paper (see Appendix Tables 3 and 4 in Supplementary material).

²⁸ Recent papers on infectious diseases are exploring the role of *viral interference*; a process where individuals infected with the swine flu could become immune to other viruses (e.g., Gröndahl et al., 2014; Ånestad and Nordbø 2011; Casalegno et al., 2010). See also Wrarmert et al. (2011) for related possibilities. Whether the H1N1 served as an “antibody” for the viruses causing diarrhea (e.g., rotavirus) goes beyond the scope of this paper.

²⁹ These numbers underestimated purchases as imports of hand sanitizers are not included. Furthermore, these data are not available at the state level.

³⁰ Although we are uncertain about the methodology, others have indicated that a survey conducted by Nielsen showed that the top two adopted measures by consumers in Mexico during the swine flu outbreak were: 1) the use of face masks, and 2) hand washing with soap and water or hand sanitizers. Nielsen also reported an increase in sales of soaps and hand sanitizers. <http://economia.terra.cl/noticias/noticia.aspx?idNoticia=200906171913.TRM.78156849>, accessed on November 24, 2013, and www.cnnexpansion.com/get_content.php?q=print&url=mi-dinero/2009/06/17/autoservicios-ganan-con-la-influenza, accessed June 11, 2013.

with higher incidence of the swine flu at the time of the survey had higher usage of hand sanitizer. This supports our hypothesis that the H1N1 pandemic changed hygiene practices, leading to more hand washing with soap or at least more use of hand sanitizers, and this change led to a reduction in hospitalizations due to diarrhea.³¹

We complement these results by showing that Mexicans became more aware of the need to have better hygiene practices and increased their demand for knowledge about preventive behaviors. Fig. 4, Panels A and B, show the trend of public interest for hand sanitizers between 2007 through 2011 using data from Google searches originated in Mexico. To understand the y-axis of Fig. 4, it is important to note that Google Trends does not release the actual number of searches but instead provides an index, which Google describes it as a measure of “relative popularity” of searches. As mentioned in the data section, the data represent an index ranging from 0 to 100.

In Fig. 4, Panel A, we show the weekly index of searches throughout 2009. The pattern is clear. Prior to week 15 (early April) there are few searches for the expression “hand sanitizer” (*gel* or *gel antibacterial* in Spanish). However, at the beginning of the swine flu outbreak in early April we observe a spike in the number of searches of more than five times relative to first weeks of the year. The post-outbreak trend remained at a level that was higher than the pre-outbreak period. We further expand this analysis in Panel B of Fig. 4 where we show the searches before and after 2009 (but keeping the index equal to 100 at week 15 of 2009). The black (solid) and blue (long-dashed) lines represent 2007 and 2008, respectively, while the top two lines capture 2010 and 2011, respectively. We show that prior to 2009, the interest in hand sanitizers was consistent for 2007 and 2008, showing only small spikes that appear to be seasonal. These seasonal patterns are repeated in 2010 and 2011; however, the magnitude of Google searches increased significantly and remained high throughout the post-2009 period.³²

We test whether this demand for knowledge is a possible mechanism by including it as an outcome in Eq. (1). We do this by constructing a panel dataset from searches by the state and year. In columns 6 and 7 of Table 5, we find a positive and large relationship between the incidence of H1N1 and Google searches. The results of column 6 indicate that 1000 cases of the H1N1 are associated with an increase of 3.2 units in Google searches for hand sanitizers and it is statistically different from zero at the 10% level using bootstrapped standard errors. This represents a substantial increase (42 percent) with respect to average value during the period of analysis (mean = 7.63). Note that due to low search volume there are no data for eight states,³³ so in column 7 we ran our regression for Google searches replacing the missing values with zeroes (the lowest possible value in the Google Trends index) for those eight states. This way, we are able to utilize the full dataset. This imputation leads to similar findings – more Google searches in areas with a higher incidence of the H1N1—and it allows us to gain precision for the estimates by “recovering” those missing values (*p*-value

³¹ Similar behavioral changes were reported during an outbreak of Severe Acute Respiratory Syndrome or SARS. See Leung et al. (2004) for details. Also, there was a spike of purchases for hand sanitizers in the United States during the swine flu in 2009 (see Appendix Fig. 3 in Supplementary material). Furthermore, some research indicates that the H1N1 pandemic led to an increase in hand washing behavior in the US (e.g., Jones and Salathe 2009; Rubin et al., 2009) making our mechanism even more plausible.

³² Similar patterns –a spike around week 19 and higher searches relative to the pre-outbreak period– can be observed for Google searches of the word “cubrebo-cas” or face masks (not shown but available upon request). Also, when dividing the sample of states by high and low levels of H1N1, we find that the spike happens in both types of states at around the same time (figure not shown but available upon request).

³³ These states are, in alphabetical order, Baja California Sur, Campeche, Colima, Chihuahua, Durango, Nayarit, Tlaxcala, and Zacatecas.

Table 5
Possible Mechanisms: 2008–2009.

	(1) State-level Expenditures	(2) Federal Expenditures	(3) Oral Rehydration Salts	(4) Vaccines	(5) Hospital Beds	(6) Google Searches ^c	(7) Google Searches ^c
H1N1/1000 ^a	0.027 (0.013)	0.006 (0.005)	−0.086 (0.062)	−0.025 (0.037)	−0.006 (0.023)	3.156 (1.134)	3.111 (1.057)
p-value ^b	0.724	0.889	0.152	0.502	0.812	0.106	0.085
R ²	0.285	0.137	0.627	0.682	0.073	0.458	0.451
Mean (\bar{Y})	8.194	5.998	14.518	14.518	6.693	7.63	5.72
Obs.	64	64	64	64	64	48	64

Notes: Each column represents a separate regression. All regressions include time and state fixed effects. Mean (\bar{Y}) denotes the mean of the dependent variable for each specification and for the period 2008–2009.

^a Parameters for columns (1)–(5) capture the association per 1000 cases of H1N1. The dependent variable in columns (6) and (7) captures the intensity of search volume per state and year, which ranges from 0 to 100. The dependent variable in columns (1)–(5) is the log of the outcome of interest. Columns (1) and (2) denote the log of millions of expenditures in Mexican pesos.

^b p-value denotes the p-value of wild bootstrapped standard errors for each specification to correct for small number (32) of clusters.

^c In columns (6) the specifications exclude the states of Baja California Sur, Campeche, Colima, Chihuahua, Durango, Nayarit, Tlaxcala, and Zacatecas for which Google data were missing. In column (7) we assigned a value of zero to states with missing Google searches.

<0.10). These analyses indicate that the main mechanism arises from the demand for knowledge regarding hygiene practices and not so much from the other channels examined above.

5.2. Effects of the seasonal flu

Our key hypothesis is that the 2009 H1N1 shocked or nudged people into changing their behavior (washing their hands) and this behavioral change led to a decline in diarrhea cases for children. Is this effect also observed with the spread of respiratory infections arising due to the seasonal flu? Theoretical models predict that engagements in preventive behavior are triggered only when the (contagious) disease crosses a threshold (Philipson 2000). Such models would predict a null effect from the seasonal flu but an important reaction from the H1N1 pandemic. To study this question we modify Eq. (1) as follows,

$$y_{st} = \alpha + \lambda \text{Flu}_{st} + \tau_t + \theta_s + \mu_{st} + \epsilon_{st}, \quad (2)$$

where y_{st} represents the hospital discharges of diarrhea for children under five in state s and year t (A00–A09X). In Eq. (2) we are interested in the effect of the seasonal flu (Flu_{st}) for all ages (similar to our H1N1 variable). We obtained these data from Mexico's SINAVE for years prior to the H1N1 pandemic (2006–2008). This variable represents morbidity cases of the seasonal flu. While both the swine and the seasonal flu could be considered as health shocks, the latter did not exhibit the unexpected magnitude and the uncertain nature of the H1N1 pandemic. Thus we can test whether small, expected health shocks (the seasonal flu) have similar effects to larger and unexpected health shocks (the swine flu). Analogous to Eq. (2), λ is the parameter of interest and as before, we control for state (θ_s) and time (τ_t) fixed effects. We also include state-specific trends (μ_{st}). The results of estimating this equation are presented in column 7 of Table 2.

Unlike the H1N1, there is no link between cases of the seasonal flu and diarrhea cases. Each case of the seasonal flu is associated with 0.003 additional cases of diarrhea but this parameter is not statistically different from zero. The spread of the seasonal flu does not have an effect on diarrhea as the 2009 H1N1 does. This evidence suggests that small and expected health shocks like the seasonal flu do not matter. Large and unexpected shocks like the 2009 H1N1 pandemic do. This evidence is consistent with theoretical models reviewed by Philipson (2000).

6. Are the effects persistent?

An important contribution of our paper is its capacity to test whether the effects continue over time. In the previous sections

we have shown that the onset of swine flu in 2009 is associated with a reduction in diarrheal diseases as measured by hospital discharges and morbidity cases. We have presented robust evidence in favor of the causal nature of these effects, thereby ruling out pre-trends affecting both H1N1 and diarrhea cases and other possible alternative explanations. While other interventions have been able to show the contemporaneous effect of information campaigns on reduction in diarrhea cases (see for examples the 14 papers reviewed by Ejemot-Nwadiaro et al. (2008) the evidence of whether those reductions would be sustained after the campaign ends is scant.³⁴ While there are papers examining the persistence of the effects of hand washing campaigns (e.g., Cairncross et al., 2005; Wilson and Chandler, 1993) they concentrate mainly on hand washing practices rather than measuring possible declines in diarrhea. Our paper represents a significant advantage as we directly test whether the 2009 pandemic led to sustained declines in diarrhea.

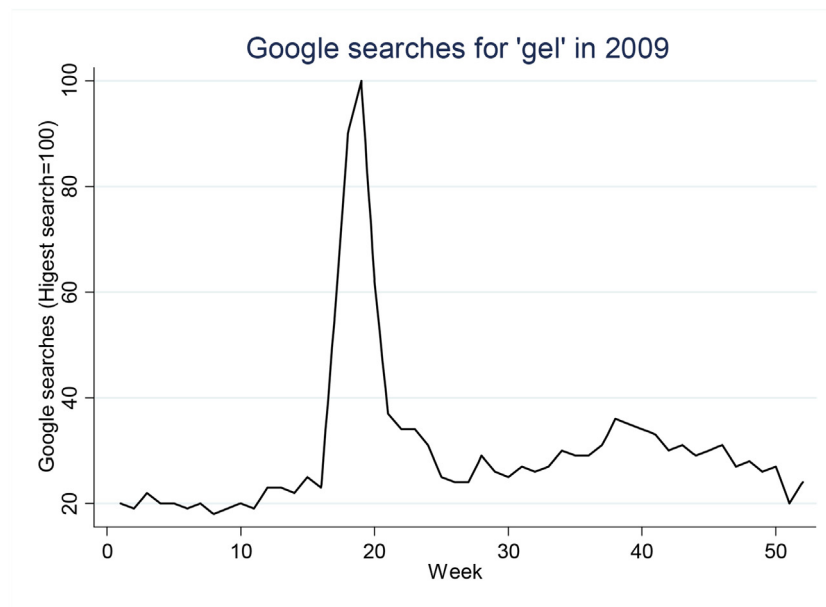
To address this issue we add more years to the control and treatment period so that our analysis includes data from 2006 to 2012. By including the years after 2009, we can test whether the subsequent years had a similar impact as 2009, and also whether the effects remain the same when there are fewer cases and concerns about the swine flu. We note that in 2009 there were over 70,000 confirmed cases of H1N1, but these numbers plummeted in the following years. In 2010, there were 2698 swine flu cases followed by only 372 in 2011 and 4507 in 2012. If the 2009 pandemic served as a “natural nudge” then the post-2009 H1N1 cases could be thought as “reminders” following the literature of behavioral economics. As reviewed by Luoto and Carman (2014), reminders have been used in several settings where agents need follow-up nudges to sustain their health-related behavioral changes.

In column 1 of Table 6, our variable of interest captures the cross-sectional and time series variation in H1N1 cases between 2009 and 2012 and as before, zero for all states and years between 2006 and 2008. In other words, we replicate Eq. (1) but with more years for both the control and the treatment periods. The coefficient of interest is −0.046, which is smaller than the coefficient of −0.105 in the main analysis. This suggests that post-2009 H1N1 cases have, on average, a smaller impact compared to the original.

We then alter Eq. (1) slightly to estimate the persistence of the 2009 effect, controlling for the contemporaneous effect of the

³⁴ An exception we are aware of is Bennett et al. (2015b) who show that an intervention combining informational sessions and microscope demonstrations led to reductions in diarrhea, which persisted 16 months after the intervention. In our case, the effects last for at least three years.

PANEL A. GOOGLE SEARCHES FOR “GEL” IN 2009



PANE B. GOOGLE SEARCHES FOR “GEL” PRE- AND POST-2009

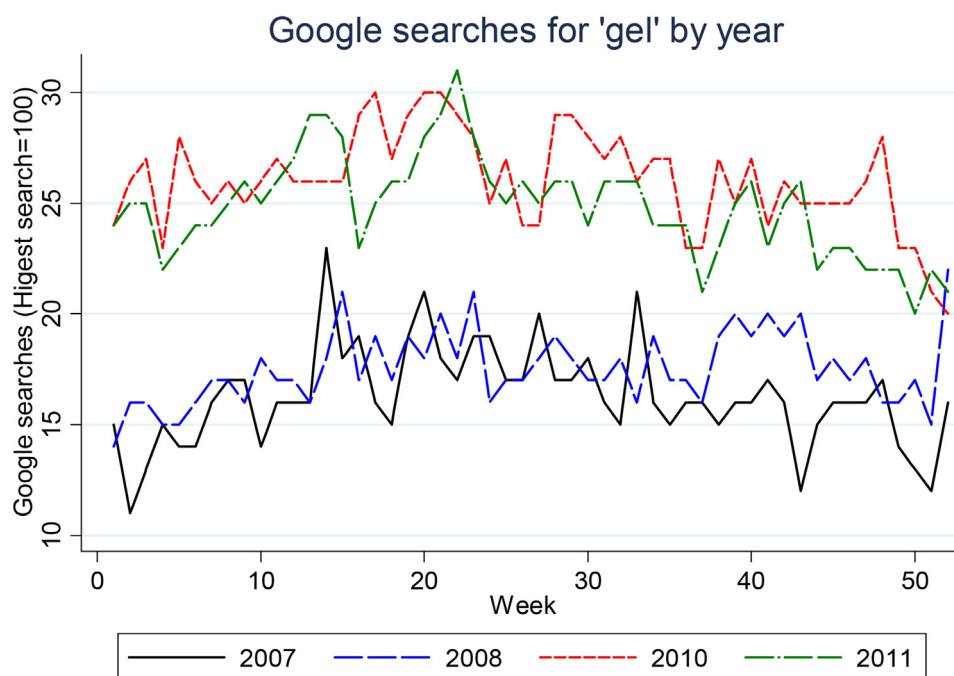


Fig. 4. Google Searches for Hand Sanitizer Information.

Panel A. Google Searches for “gel” in 2009.

Pane B. Google Searches for “gel” pre- and post-2009.

Sources: Authors' analysis of data on internet searches for the Word “gel” in Mexico from GoogleTrends (<https://www.google.com/trends/>).

H1N1. This is formally shown in Eq. (3) where we add the 2009 cross-sectional variation $-H1N1_{2009_{st}}$ and assign it to that and all the subsequent years (and zero between 2006 and 2008). Thus,

the parameter ρ measures the *persistence* of the 2009 swine flu on diarrhea cases:

$$y_{st} = \alpha + \beta H1N1_{st} + \rho H1N12009_{st} + \tau_t + \theta_s + \mu_{st} + e_{st}. \quad (3)$$

The results of estimating Eq. (3) are shown in column 2 of Table 6. We find evidence of a persistence effect: an increase in cases of the 2009 H1N1 is associated with a decline in the number of diarrhea cases for children under five. For every case of the 2009 H1N1 we observe 0.221 fewer cases of diarrhea, even after controlling for contemporaneous cases of H1N1 (p -value = 0.024). Furthermore, note that the contemporaneous effect of H1N1 is now positive (but not statistically significant based on the bootstrapped p -value). This positive sign is not surprising in the absence of behavioral change since 13 percent of the swine flu cases were associated with diarrhea as one of the symptoms. This reinforces our hypothesis that it is the actual health shock of the 2009 H1N1 pandemic that triggered the behavioral change.

Next, we consider an event study by replacing the H1N1 variable in Eq. (3) with four interaction terms of this variable with binary indicators for each year in the period 2009–2012. This allows us to evaluate the contemporaneous impact of each year separately. Likewise, if the contemporaneous effect exists only in 2009 and disappears with future H1N1 cases this would be evidence of a nudge: people adjusted their behavior in the presence of a new shock. The shock allowed them to reach an equilibrium behavior in the sense that future shocks no longer change their hygiene practices. Now consider a situation where the first nudge changed behavior, but it did not lead to an optimal solution. In this case, there is still “room for improvement” and further “reminders” are needed to foster improvements in the production of health outcomes. In this case, it seems possible that further nudges could have larger, or smaller, effects than the first nudge depending on the degree of dynamic complementarities between nudges in periods 1 and 2.³⁵

The results are presented in columns 3 and 4 of Table 6. Column 3 indicates that the effect is negative in both 2009 and 2010 but with larger effects for the latter. The results, however, disappear with the 2012 H1N1. These findings suggest that further reminders help reducing diarrhea cases but for a limited time. Most importantly, in column 4, and analogous to column 2, when accounting for the persistence effect of the 2009 pandemic, we find that the contemporaneous effects become substantially less relevant –much smaller in magnitude and no longer statistically different from zero– but the 2009 effect remains. These results suggest that as a health shock, the 2009 H1N1 pandemic had a contemporaneous and a long-lasting effect in the reduction of diarrhea cases of young children.

7. Conclusion

This paper shows that severe health shocks such as the H1N1 pandemic in Mexico led to a long-lasting improvement in health outcomes by reducing diarrhea cases among young children. Several placebo and robustness checks validate our difference-in-difference identification strategy and strengthen the interpretation of our estimates as causal. While other mechanisms are possible, we present evidence supporting the hypothesis that the pandemic was a shock that induced changes in hygiene practices and motivated people living in areas with higher prevalence of the swine flu to acquire information about better hygiene practices and to wash their hands or increase their use of hand sanitizers.

These findings expand our knowledge of health economics in several ways. First, as reviewed by Cawley and Ruhm (2012), previous studies emphasizing the role of health behaviors as key inputs

³⁵ When the H1N1 impacts become larger for all periods after 2009 an alternative explanation could come from structural changes in the health system or mass vaccinations. However, we do not observe such pattern in the post-2009 analysis. Furthermore, we have already ruled out vaccinations as a possible mechanism in section 5.1. We thank an anonymous referee for this insight.

Table 6

Persistence of the 2009 Effects of H1N1 Prevalence on Intestinal Infections (A00–A09X) for Children Under Five: 2006–2012.

	(1)	(2)	(3)	(4)
H1N1	−0.046 (0.030)	0.068 (0.042)		
p-value	0.185	0.138		
H1N1*2009		−0.221 (0.058)		−0.195 (0.067)
p-value		0.024		0.075
H1N1*2009			−0.045 (0.030)	0.056 (0.045)
p-value			0.156	0.241
H1N1*2010			−0.533 (0.305)	−0.109 (0.332)
p-value			0.050	0.614
H1N1*2011			−0.614 (2.201)	−0.270 (2.152)
p-value			0.644	0.749
H1N1*2012			0.455 (0.392)	0.265 (0.388)
p-value			0.379	0.539
R ²	0.781	0.799	0.789	0.800
Mean (\bar{Y})	1,075	1,075	1,075	1,075
Observations	224	224	224	224
State Trends	Yes	Yes	Yes	Yes

Notes: The period of analysis is 2006–2012. All specifications include time and state fixed effects. The dependent variable is the annual number of hospital discharges where the primary diagnosis was International Classification of Diseases (ICD-10) codes A00–A09X (Intestinal Infections) for children under the age of 5. H1N1 is equal to the number of confirmed H1N1 cases in 2009–2012, and zero for 2006–2008. H1N1_2009 is defined as the number of confirmed H1N1 cases that occurred in 2009 for years 2009–2012 and zero for years 2006–2008. H1N1*2009, H1N1*2010, H1N1*2011, and H1N1*2012 denote the interaction of H1N1 and a dummy variable for 2009, 2010, 2011, and 2012, respectively. p -value denotes the p -value of wild bootstrapped standard errors for each of the specification to correct for small number (32) of clusters. Mean (\bar{Y}) denotes the mean of the dependent variable for each specification. State Trends denote state-specific linear trends.

in the production of health outcomes have focused on chronic rather than infectious diseases and on advanced economies instead of developing countries. In that regard, by focusing on gastrointestinal infections in Mexico, our study expands our knowledge of the role of behavioral changes in a much less investigated setting and addresses an important gap in the literature. Second, the fact that the 2009 pandemic matters for behavioral change, compared to the null effect found from the smaller (and more predictable) seasonal flu, provides empirical support for theoretical models where a decision to engage in preventive behavior is triggered only when the (contagious) disease crosses a threshold (e.g., Philipson 2000). Furthermore, our paper complements recent advances in behavioral economics by exploring how health shocks, such as pandemics, can act as “natural nudges” that affect the production of health outcomes and generate long-lasting effects.

Our findings raise several issues regarding policy implications. First, we show that business-as-usual strategies, such as overall government health expenditures, vaccinations campaigns as well changes in infrastructure (e.g., hospital beds) are unlikely to be behind the reasons for the decline in diarrhea cases.³⁶ During major health emergencies, such as pandemics, individuals increase their demand for knowledge about ways to remain healthy (e.g. learning about better hygiene practice increases). If governments facilitate access to low cost information sources, such as search engines, (or hot lines, TV or radio spots), especially in areas where the disease is more prevalent, our results indicate that the public will use these resources to acquire information. In that setting, health outbreaks

³⁶ Data limitations prevent us from examining the impact of specific government informational campaigns as well as other preventive measures.

or emergencies could have unanticipated positive effects as long as the population is willing to change behaviors under the appropriate environment, e.g., with adequate information, incentives, and social acceptability.

Furthermore, our results from Google searches indicate that agents seek information broadly by using search engines. Thus, the information to help address their demand does not need to be provided exclusively by the government. During these emergencies, profit-seeking firms could provide a public health service too. This is consistent with the points made by Ippolito and Mathios (1990, 1995) indicating that when producers are allowed to reveal the advantages of their products, firms could provide key information to consumer who then react to this news. For example, producers and sellers of hand sanitizers or other products that improve hygiene practices could complement government efforts by advertising the benefits of their products, especially when government's health budgets are small as in the case of many developing countries. An open research question is whether market friendly policies, such as low entry costs, could complement government efforts during health emergencies by allowing more firms to enter the market and supply the demand for health products that consumers are seeking, as shown by our findings.

Finally, health shocks such as the swine flu, HIV or cancer must be considered "high-water marks" as indicated by Smith et al. (2001) regarding the effectiveness of information campaigns. Therefore, the question remains whether it is indeed possible to design information messages that could alter and sustain health behaviors analogous to the effects of the H1N1 pandemic in Mexico, but without the obvious adverse consequences of a health emergency. A possible way to identify these messages could be found in the marketing strategies implemented in another Latin America country, Uruguay, as part of a nationwide antismoking campaign. Harris et al. (2015) find that the inclusion of warning messages in cigarette packages, showing explicit pictograms of newborns affected by smoking during pregnancy, led to a higher smoking cessation for the targeted population of pregnant women. Future research, should explore whether an analogous system of effective messages could be applied to the context of promoting long-lasting and improved hygiene practices.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.jhealeco.2017.03.008>.

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