Over-the-Counter Access Regulations: Evidence from an Antibiotics Law in Mexico*

Adrian Rubli
Brown University

April 2017

Regulations restricting over-the-counter (OTC) access to drugs are important policy tools for mitigating self-medication and encouraging doctor visits. However, they may have unintended consequences when access to affordable healthcare is lacking. This paper estimates the effect of a law restricting OTC sales of antibiotics in Mexico on public hospital admission rates. I find a temporary but significant decline of around 40% in admission rates due to infections. This effect is driven by viral infections, adult patients, and patients from higher education municipalities. OTC regulations may inadvertently increase the socioeconomic health gradient unless accompanied by policies that expand affordable healthcare.

JEL codes: I11, I18, I15
Key words: over-the-counter access, supply regulations, self-medication, antibiotics, health gradient

*A previous version of this paper circulated as "Supply Regulations in the Market for Medicines: Evidence from an Antibiotics Law in Mexico". I thank Anna Aizer, Nathaniel Baum-Snow, Andrew Foster, Sriniketh Nagavarapu, Emily Oster, and Anja Sautmann, as well as participants at the 2015 LACEA meeting and the 2015 NEUDC conference for helpful comments and suggestions. I acknowledge financial support from the Brown University Department of Economics and the Population Studies and Training Center at Brown University for the acquisition of antibiotic sales data (NIH, P2C HD041020 and T32 HD007338). All remaining errors are my own. adrian_rubli@brown.edu

1 Introduction

Self-medication and, as a consequence, the misuse and overuse of medical drugs entail various costs. There are private costs that stem from individuals misdiagnosing themselves, which can lead to preventable complications (Ruiz, 2010; Wolff, 1993). These risks may not be fully known by individuals. There are also social costs associated with the negative externality of drug-resistant pathogens, which individuals typically fail to consider (Neu, 1992; Chopra and Roberts, 2001; Okeke et al., 1999). Policy-makers have suggested and implemented diverse strategies to curb this misuse (WHO, 2002). This paper focuses on supply-side interventions, specifically by restricting over-the-counter (OTC) access to drugs.

These gate-keeping policies seek to limit patient access to medications, by requiring a formal healthcare provider to prescribe the drugs.[1] OTC access regulations carry ancillary costs that have not been analyzed in the literature. If affordable healthcare is not widely available, these regulations impose an additional cost on individuals. Those who are unable to absorb it may end up forgoing treatment altogether. As such, the benefits, in terms of individuals switching from self-medication to formal healthcare, may not necessarily outweigh the costs, in terms of paying for a doctor. The distribution of these benefits and costs is context-specific, and there is no guarantee that such a policy will be welfare-improving across the entire population, or how the net effects might be distributed throughout.[2]

This paper characterizes the tradeoff between these benefits and costs, by analyzing the impact of an OTC access regulation in Mexico on health outcomes. On August 25, 2010, the

[1] In an ideal scenario, professional providers follow checklists when diagnosing, decreasing medication overuse. However, this requires incentives between patients and providers to be correctly aligned, the absence of information asymmetries, and the lack of faulty communication between doctor and patient, which the literature has shown is hardly the case. For examples on supplier-induced demand and its relationship to deficient doctor-patient communication see De Jaegher and Jegers (2001), Currie et al. (2011), and Bennett et al. (2010). In terms of information asymmetries, Schottmüller (2013) and Pauly and Blavin (2008) provide theoretical results regarding optimal information flows between doctors and patients. Despite these imperfections, the general consensus is still that physicians provide better healthcare than self-medication (Chang and Trivedi, 2003). Therefore, this paper abstracts from the specific quality attributes of formal care in this particular setting.

[2] This argument is similar to the rational epidemics model proposed by Geoffard and Philipson (1996) and the differential behavioral responses of individuals to HIV analyzed, among others, by Kremer (1996) and Oster (2012).

Mexican government implemented a law at the national level that prohibited OTC sales of antibiotics. Prior to that, almost half of all antibiotics sold at private pharmacies occurred without a prescription (Wirtz et al., 2007). After this regulation, sales of antibiotics declined around 30% (Santa-Ana-Tellez et al., 2013).

Using hospital discharge data from 2007 to 2014 from all public hospitals administered by the Department of Health (SSA), I analyze the effect of the antibiotics law on hospitalization rates due to infections.[3] These data only allow me to identify effects on illnesses that required inpatient care. As such, I provide estimates on an extreme measure of morbidity. I identify the effect of the regulation through an event study design, analyzing changes within hospitals over time on either side of the law's implementation date. The high frequency data and how the regulation was introduced support a causal interpretation of the findings.

The main result shows that admission rates due to infections temporarily declined about 40% within a public SSA hospital over time. This effect occurs gradually over the first six weeks after the OTC access regulation, with rates resuming pre-law levels by 12 weeks after implementation. I interpret the short-lived effect as the result of other changes in healthcare provision as a response to the law, such as pharmacies opening their own doctors' offices to boost antibiotic sales (Pérez-Cuevas et al., 2014; FUNSALUD, 2014; Rubli, 2017). I also show placebo checks for causes unrelated to infections and antibiotics (namely, strokes and mental illnesses), as well as a series of robustness checks that support this result.

I then decompose this main finding by type of infection. Results show that the majority of the effect is due to changes in admission rates due to viral infections, while bacterial infection hospitalization rates remain mostly flat around this date. I argue that when individuals are biased towards self-medicating with antibiotics, regardless of the type of infection, the mismatch between self-treatment and what a doctor would prescribe is greater for viral

[3]Healthcare in Mexico is divided into a public and private sector. Public healthcare is further divided into various institutions, each with their own set of affiliates and network of providers. Informal workers and the unemployed are covered by the SSA, while formal workers are affiliated to the Mexican Social Security Institute (IMSS). See Appendix A for more details on the Mexican healthcare system.

diseases. As such, there is more to gain from incentivizing doctor visits in the case of viral infections.

I also explore heterogeneous effects by age, with the majority of the result driven by patients between the ages of 15 and 64. According to the 2006 National Health Survey (ENSANUT), self-medication rates are higher for these individuals. Therefore, this finding validates the interpretation that the main result is indeed due to the effect of the regulation on individuals who were previously self-medicating, and not due to information effects through the salience of these health issues around this time.

Lastly, I decompose the effect by education characteristics of the patients' municipality of residence. Classifying patients into those that live in municipalities with above and below average schooling measures, I find that the result is driven mostly by the former. This is consistent with the idea that only individuals who are able to absorb the additional cost of seeing a doctor will actually switch from self-medication to formal healthcare. Therefore, OTC access regulations may exacerbate the socioeconomic health gradient in settings where affordable healthcare is not universally available.

To the best of my knowledge, this is the first paper to quantify the effect of OTC access regulations' ancillary costs on the distribution of potential benefits. This paper makes two contributions to our understanding of supply-side interventions to combat self-medication. First, I show that infections for which there is a greater mismatch between self-treatment and physician-prescribed treatment are the ones for which there is a greater improvement in health outcomes, since individuals are worse at treating these diseases on their own. Second, I show that the gains from OTC restrictions are only experienced by patients from municipalities from the right-hand side of the socioeconomic distribution. Therefore, regulations unaccompanied by policies that extend access to affordable healthcare may lead to an unintended widening of the socioeconomic health gradient.

The rest of the paper is organized as follows. Section 2 develops a simple framework to guide the discussion and presents the background on the antibiotics law in Mexico. Section 3

explains the data and outlines the empirical strategy. Section 4 presents the main results and robustness checks. Section 5 explores heterogeneous effects. Section 6 concludes.

2 Background

This section begins by laying out a general framework that guides the paper and facilitates the interpretation of the results. See Appendix C for a more rigorous development of a simple theoretical model in this context, and Chang and Trivedi (2003) for a general approach to modeling the demand for self-medication. I then provide details on the antibiotics law introduced in Mexico in August of 2010.

2.1 Conceptual Framework

Individuals generally have three options when they get sick: seek professional medical care, self-medicate or do nothing (where nothing should be thought of as basic, non-medicinal home remedies). Physicians are better at diagnosing than individuals, but are more costly in terms of money and time. Doing nothing is the cheapest option, but has the lowest chances of restoring health and/or longest time of recovery. These tradeoffs between costs and benefits (in terms of replenishing health stocks) inform the decision that each person makes.

As such, individuals sort into professional healthcare, self-medication, and doing nothing based on affordability, both in terms of the actual cost of each option as well as the opportunity cost of not getting better. Along some dimension of socioeconomic status, individuals from the left tail of the distribution are more likely to do nothing, individuals from the right tail are more likely to get professional medical attention, and those in the middle are more likely to self-medicate.[4]

[4] In a theoretical setup where the only alternatives are self-medication and formal healthcare, Chang and Trivedi (2003) shows that the poor are more likely to self-medicate and that the law of demand for self-medication holds, implying that OTC access increases self-medication rates, and that affordable healthcare decreases self-medication.

Self-medication is problematic since individuals are less able to diagnose themselves, and because abusing medications has potential negative externalities, such as fostering bacterial resistance to antibiotics (Ruiz, 2010; Neu, 1992). Governments and international organizations are therefore interested in combatting self-medication (WHO, 2002). One possibility is limiting OTC access to drugs, with the goal of forcing individuals to seek professional healthcare when sick.[5]

Once these regulations are introduced, individuals who were self-medicating now need to reconsider their choice. Individuals that are too far to the right and left of the distribution are unaffected since they were not self-medicating anyway. From the segment that was previously self-medicating, those who can afford it will tend to switch towards physician care, while those that cannot will have to switch to doing nothing. This problem is exacerbated in contexts where affordable healthcare is lacking.

Therefore, the net effect of these regulations depends on whether more people now choose professional care over nothing. Health outcomes in the population will improve as long as there is a greater proportion of individuals who were self-medicating that are now going to the doctor than doing nothing. However, this regulation will result in winners and losers. The former are individuals successfully nudged into seeking medical care, while the latter are those who are unable to afford it. This may imply unintended consequences in terms of increasing the socioeconomic health gradient.

Lastly, consider differences in the effect of these regulations based on type of illness. It is safe to assume that individuals have a strong bias towards consuming antibiotics, regardless of the nature of the infection.[6] If individuals default to self-medicating with antibiotics when sick, then the mismatch between self-treatment and treatment prescribed by a physician is

[5]Increasing doctor visits is an important goal, since many conditions, for example hypertension, are diagnosed during unrelated doctor visits (WHO, 2013; Fisher-Hoch, 2012).

[6]For the US, Barnett and Linder (2014a) shows that the rate of prescriptions for antibiotics for acute bronchitis were around 71% in 2010, although scientific evidence shows they should be zero for this disease. Additionally, antibiotic prescribing rates for sore throats caused by group A streptococcus are around 70%, although the prevalence of this bacterium is just 10% (Barnett and Linder, 2014b). For Mexico, patient-induced demand for antibiotics is described by Wirtz et al. (2007) and Dreser et al. (2008).

larger for viral infections than bacterial ones. This implies that there is more to gain from seeking professional medical care when a patient has a viral infection than when it is bacterial, and consequently, any welfare gains after an OTC access regulation should be more prevalent for the former.

2.2 The Antibiotics Law in Mexico

The regulation of antibiotic use in Mexico was very lax prior to 2010. The law stated that pharmaceutical companies should print warning labels on antibiotic packaging, explaining that a medical prescription was required. However, there was no legal enforcement to accompany this statement. As Dreser et al. (2008) explains, antibiotics were easily and commonly bought OTC. Wirtz et al. (2007) estimates that 46% of antibiotic sales occurred without a prescription before 2010. A natural consequence of this lack of regulation was a high rate of self-medication and medically unjustified consumption, as outlined in Wirtz et al. (2008).[7]

In 2009, Mexico was severely affected by the influenza AH1N1 epidemic, caused by a mutation originating from the type A influenza virus. The first case appeared in late March 2009, and a month later the World Health Organization (WHO) had declared it a level 6 pandemic.[8] The extent of the outbreak was aggravated due to the population's tendency to self-medicate with antibiotics, which had no effect on the virus and led to severe complications or even death.

As a response to the complications from mishandling the epidemic, the federal government announced a law in May 2010 that would strictly enforce the sale of antibiotics by

[7]The high prevalence of antibiotic use in any context is correlated with bacterial resistance. Although the World and Panamerican Health Organizations have long recommended prudent use of antibiotics, there is a surprising lack of data and research with respect to the level of bacterial resistance in Mexico. See Rodríguez-Noriega et al. (2014) for a general overview of the existing medical literature in the Mexican context. According to this literature, bacterial resistance in Mexico (focusing on the most common bacteria that lead to respiratory and gastrointestinal diseases) ranged from 20 to 50% during the 1990's and 2000's.

[8]For detailed accounts on the development of the pandemic, measures of prevalence, mortality and morbidity, behavioral responses, and other medical information, see Domínguez-Cherit et al. (2009); Chowell et al. (2011); Elizondo-Montemayor et al. (2011); Pérez-Padilla et al. (2011) and Agüero and Beleche (2016). The official government report, available at http://www.epidemiologia.salud.gob.mx/doctos/infoepid/publicaciones/2011/monografias/p_epi_pandemia_ifluenza_%20A_H1N1_2009_Mexico.pdf contains further details.

prescription only.[9] According to this regulation, pharmacies would now have to keep the original prescription form (with patients retaining a carbon or photostatic copy), and would be constantly audited for compliance. Sanctions for nonconformity with the law were established at up to 16,000 times the legal minimum wage (in Mexico City, up to 876,800 pesos or 73 thousand US dollars). This law came in effect three months after it was announced, on August 25, 2010.[10]

Anecdotal evidence on compliance with the law, mostly from newspaper articles in late 2010, indicates that a vast majority of pharmacies did adhere to the new regulation. Furthermore, by December 2010 antibiotic sales had dropped by 35 to 40% according to most reports. Santa-Ana-Tellez et al. (2013) estimates the impact of this regulation on antibiotic sales and shows that they decreased by 30% between 2007 and 2012, also finding that antihypertensives - unaffected by the law - did not experience any changes. Additionally, Wirtz et al. (2013) and Wirtz et al. (2010) calculate that between 1997 and 2009, antibiotic consumption in Mexico decreased slightly over time, without any sharp breaks, lending support to the notion that the effect in 2010 is not due to other underlying trends.

Figure 1 uses penicillin sales data to show that the law indeed affected antibiotic consumption. These data come from a leading consulting firm, Knobloch Group, recording monthly sales from 2010 to 2012 for 672 urban markets (almost all urban markets correspond to full cities, although larger cities like Mexico City are divided into multiple markets). The solid light-colored line shows the log of the average volume of penicillin sold by month in an urban market. As expected, antibiotic sales are highly seasonal, with sales declining over the spring and summer months. To account for this, I first regress log sales on indicators for each month and obtain the residuals. Then I calculate a regression of these residuals on a vector of leads and lags of August 2010 and urban market fixed effects. The coefficients

[9]This law actually includes a few other medications for which prescriptions would now be strictly enforced. However, antibiotics make the bulk of these drugs and are largely considered to have been the main target of the law (Santa-Ana-Tellez et al., 2013). It should also be noted that Mexico did have a strict regulation concerning controlled substances prior to 2010 (for example, strong painkillers, such as opioids, and psychiatric drugs).

[10]Note that the implementation occurred at the national level on the same date.

of this regression are also shown in Figure 1. These results indicate an important decline in the sale of penicillin from August to September 2010.

Though one may argue that the government's objective with the antibiotics law was to lower bacterial resistance to antibiotics, it is well known in the medical literature that this effect is difficult to attain in the short run (Andersson and Hughes, 2010; Schrag and Perrot, 1996). Bacterial resistance is mostly thought of as a non-renewable resource, in the sense that the rate at which bacteria develop resistance is much faster than the rate at which resistance is lost (Laxminarayan and Brown, 2001). Dreser et al. (2012) analyzes media coverage and public service announcements around 2010 in Mexico, and finds that the government's main concern was the private risks of self-medication, with bacterial resistance playing a minimal role.[11]

3 Data and Empirical Strategy

3.1 SSA Hospitalizations Data

This paper uses publicly available hospital discharge data from all public hospitals administered by the Department of Health (*Secretaría de Salud*, SSA). The data cover a total of 821 SSA hospitals. Public healthcare in Mexico is provided by different separate institutions, each with their own target population and network of providers. Formal workers are covered by the Mexican Social Security Institute (IMSS), workers of the informal economy and the unemployed are affiliated to SSA through the *Seguro Popular* program, and workers of the state, army, marines and national oil company have their own separate healthcare institutions.

[11] Furthermore, it is essential to understand that the discussion that led to this law stemmed from the inappropriate self-medication that exacerbated the 2009 influenza pandemic. Therefore, it seems more precise to think that the government's goal was to control the misuse of medication, particularly antibiotics, mainly by forcing the population to see a doctor instead of simply having OTC access to these drugs. In the literature, accessing better healthcare has been linked to better outcomes such as higher productivity and school attendance. See for example Adhvaryu and Nyshadham (2012).

According to the 2006 ENSANUT, 46% of the population was covered by the public system (28% by IMSS and 11% by SSA), 1% were privately insured, and the remaining 53% were uninsured.[12] The same survey reveals that 79% of all hospitalizations occur at a public hospital, with 38% at IMSS, 29% at SSA, and the remaining 12% at the other smaller public institutions (for more details on the Mexican healthcare system, see Appendix A).

Observing only SSA hospitalizations implies a selected sample based on sociodemographic characteristics. As such, SSA patients are more likely to be informal workers, lack formal insurance, and have a lower income. According to the 2006 ENSANUT, patients receiving inpatient care at SSA hospitals are on average younger, more likely to be female, indigenous, illiterate, are on average less educated, and have a lower income. This selected sample is of particular interest, since they are the most vulnerable and most likely to be affected by the tradeoffs introduced by the antibiotics law, and as such are relevant and informative to economists and policy-makers alike.

Each observation in this dataset corresponds to a patient, for which admission and release dates are recorded, as well as the initial and final diagnosis (according to the International Statistical Classification of Diseases and Related Health Problems, ICD-10). Patient characteristics, namely, sex, age, and municipality of residence, are also observed.[13] For each year, there are over 2.5 million SSA hospitalizations.

I divide hospitalizations into bacterial and viral infections, based on the ICD-10 classification codes for the final diagnosis. Whenever it was unclear whether the illness was caused by a bacterium or a virus, neither was chosen. All infections are then constructed as either bacterial or viral, ignoring other types such as parasitic infections. For a detailed account of the diseases under each category, see Tables B1 and B2 in Appendix B. As a placebo check, I also quantify hospitalizations that are entirely unrelated to antibiotics and infections. For

[12]The next round of the ENSANUT, carried out in 2012, reveals that six years later, 73% were covered by public insurance, 1% by private insurance, and the remaining 26% were uninsured. These numbers are the consequence of expansions in the *Seguro Popular* program.

[13]Administratively, Mexico is divided into 32 states, which are further divided into municipalities (2,456 in the entire country).

this exercise, I consider cerebral infarctions and mental illnesses.[14] For each hospital, I assign the 2010 population at the municipality level in order to construct admission rates.

Lastly, I use census data from 2010 to construct schooling measures by municipality. For each municipality, I register the fraction of the population 12 years old and over that has no schooling. Based on the proportion of the population that has no schooling, basic schooling, high school and equivalents, and college, I calculate an imputed average of years of schooling for the population ages 12 and over in each municipality.[15] Using these measures of schooling, I classify municipalities into those that fall below and above the mean.

Unfortunately, these data only allows me to identify effects on illness that eventually led to hospitalizations. Most antibiotic usage and self-medication is related to respiratory and gastrointestinal infections, and it is naturally difficult to think that a large number of these cases will end up with inpatient treatment. Nevertheless, hospitalizations provide an extreme measure of the impact of the antibiotics law on health.

Table 1 shows descriptive statistics for the full sample as well as by age groups and by schooling. In terms of age, the sample is divided into small children ages 0-4, older children ages 5-14, adults ages 15-64, and older individuals ages 65 and over. The schooling measures are based on the municipality of residence as described above, with indicators for below and above the mean. Panel A shows individual characteristics based on the 2006 ENSANUT. The insurance variables indicate that over 50% of the total population is uninsured, and that this proportion is larger among younger individuals and in municipalities with low schooling.

Likewise, 40% of the total population admits to self-medicating during the last sickness spell, and this fraction is greater among adults and older children, and in low schooling municipalities. Figure 2 plots the relationship between age and self-medication for all indi-

[14] In terms of the ICD-10 codes, cerebral infarctions are code I63, while mental illnesses correspond to F00-F99.

[15] Based on the education system in Mexico, I assign zero years for no schooling, 9 years for basic schooling, 12 for high school and equivalents, and 16 for college. Results are robust to changing the imputation to 6 years for basic schooling. These measures of schooling correlate well with other variables on socioeconomic status taken directly from the census.

viduals ages 0 to 80. This plot shows that these variables follow an inverted U shape, with self-medication rising to its maximum level by age 20 and then steadily declining.

Panel B in Table 1 shows hospital admission rates at SSA hospitals per 100,000 individuals from 2007 to 2014, for the full sample, by age groups, and by schooling of the municipality of residence. In general, hospitalization rates due to viral infections are larger than those due to bacterial infections. Note that the all infections category includes only bacterial and viral infections.

3.2 Empirical Strategy

The main specification follows an event study design, as the rollout of the antibiotics law was immediate throughout the country. I follow two approaches. The first exercise simply asks whether, within a small time window around August 25, admission rates after this date are different in 2010 relative to other years. Specifically, I estimate:

$$r_{hd} = \beta_1(\mathbb{1}_{[w \geq e]} \times \mathbb{1}_{[y=2010]}) + \beta_2 \mathbb{1}_{[w \geq e]} + \gamma_w + \lambda_y + \theta_h + \varepsilon_{hd} \tag{1}$$

where r_{hd} is the SSA hospital admissions rate at hospital h on weekly date d, $\mathbb{1}_{[\cdot]}$ is the indicator function, e is the week containing August 25, γ_w is a week fixed effect, λ_y represents indicators for each year, θ_h is a hospital fixed effect, and ε_{hd} is the idiosyncratic error term. Standard errors are clustered at the hospital level.

The coefficient β_2 in equation 1 indicates on average how admission rates change after August 25 in any given year relative to pre August 25 weeks, while the coefficient β_1 indicates the additional change post August 25 in 2010. The effect attributed to the law is therefore given by β_1, while $\beta_1 + \beta_2$ indicates the jump from before to after August 25, 2010. The fixed effects imply that the coefficients are identified off of variations within hospitals, accounting for weekly seasonality as well as level changes from year to year.

The main results restrict the data to a time window of 12 weeks before and after the week containing August 25. Furthermore, I exclude 2009 from the main analysis, due to the AH1N1 epidemic. However, robustness checks indicate that the results hold under alternative window sizes as well as when including the 2009 data. Since the data consider weekly hospitalization rates for specific diseases (namely, all infections, bacterial, and viral infections), there is a mass at zero for the dependent variable. A potential concern is that the results are driven by this mass. Therefore, an additional robustness exercise estimates equation 1 using a left-censored Tobit model.

The second exercise imposes a more demanding specification that includes a vector of lags and leads around the date of the law and uses the full dataset instead of the 12 week window on either side. This approach is slightly less parametric and is more consistent with traditional event study designs. The identification strategy is given by:

$$r_{hd} = \mathbb{1}_{[d-E\leq -K-1]}\alpha_{-K-1} + \sum_{k=-K}^{K} \mathbb{1}_{[d-E=k]}\alpha_k \quad + \mathbb{1}_{[d-E\geq K+1]}\alpha_{K+1} + \eta_d + \theta_h + \nu_{hd} \qquad (2)$$

where r_{hd} is the SSA hospital admissions rate at hospital h on date d, E is the date of the event, August 25, 2010, K is a natural number that defines an arbitrary size for the vector of leads and lags, η_d is a date fixed effect, and ν_{hd} is the idiosyncratic error term. Standard errors are clustered at the hospital level.

The coefficients of interest from estimating equation 2 are given by α_k, with k ranging from $-K$ to K. This specification analyzes whether within a hospital over time, admission rates change after the antibiotics law. Keeping in line with the previous strategy, the results are shown for $K = 12$, although the findings hold for alternative definitions. Once again, 2009 is excluded, although results are robust to including those data.

In order to interpret β_1 and α_k as causal effects of the antibiotics law, it must be that this regulation is as good as random in equations 1 and 2, respectively. The underlying assumption is that the only difference on either side of the August 25 date is the existence

of the law. I argue that the high frequency data and the circumstances surrounding the announcement and implementation of the law justify this assumption. Additionally, seasonality is accounted for by including time fixed effects (week and year in equation 1, and date in equation 2). Lastly, I present estimates for causes unrelated to the antibiotics law in order to show that there was no underlying change in supply or demand at the SSA hospitals around this time.

4 Effect on SSA Hospital Admission Rates

This section presents the main findings for the effect of the antibiotics law on SSA hospital admission rates due to infections. Table 2 shows the results from estimating equation 1. As outlined above, the dataset is restricted to 12 weeks on either side of the week containing August 25 for all years, and data for 2009 are dropped. The main results are shown in columns 1-3. The first column indicates that there is a significant and negative effect of the antibiotics law on admission rates for all types of infections. Specifically, over the 12 weeks after the law was introduced in 2010, there is on average a 41% decline in admission rates for all infections relative to the average post August 25 levels in other years. These results hold when decomposing the data into bacterial and viral infections, although a greater portion of the result is attributed to the latter.

Following a slightly less parametric strategy that analyzes dynamics around the week of the law, Figure 3 shows the coefficient estimates for equation 2. This graph plots the estimates for the lags and leads, with a 95% confidence interval. Figure 3a corresponds to the effect on admission rates due to all infections. All estimates prior to the week of the law are close to zero and not significant. After the law, there is a gradual decline in admission rates, with the largest magnitude at around 6 weeks after the law. Afterwards, the coefficients trend back upward.

Figure 3b decomposes the results by types of infection. The estimates for bacterial admission rates are small in magnitude and statistically indistinguishable from zero, and follow a relatively flat pattern throughout this time frame. The coefficients for viral admission rates show a similar pattern to the results for all infections: relatively flat prior to the law, a gradual decline up until 6 weeks after the law, and finally a trend back to zero from weeks 7 to 12. Overall, Figure 3 indicates a temporary decline in admission rates of 48% for all infections six weeks after the law, which can be decomposed into a 44% decline attributed to viral infections and a non-significant 4% due to bacterial infections.[16]

These results suggest that limiting OTC access to antibiotics resulted in a short-lived decline in hospitalization rates due to infections. This is consistent with individuals being forced to seek professional medical care when sick instead of relying on self-medication, therefore resulting in better health outcomes (less severe complications leading to hospitalizations). This effect is more prevalent in viral infections, where the mismatch between the correct treatment and the tendency to self-medicate with antibiotics is larger.[17]

The observed gradual decline is consistent with the biology of infections, since severe complications from the wrong treatment take a few weeks to develop. This pattern is also consistent with the possibility of individuals stockpiling antibiotics for self-medication in the weeks between the announcement of the law and its implementation. The fact that the effect is not permanent is possibly related to individuals seeking other alternatives to professional medical care. For example, after this law was introduced, pharmacy-adjacent doctors' offices saw a rapid expansion, mostly as a response to the decline in antibiotic sales (Pérez-Cuevas et al., 2014; FUNSALUD, 2014; Rubli, 2017).

[16]Calculated in terms of the average admission rates for viral and bacterial infections separately, this amounts to a 65% decline for viral infections, and a statistically insignificant 13% decline for bacterial infections by week six after the law.

[17]I also estimate the results on length of stay using the same strategy. However, results are noisier and hence more difficult to interpret. They do suggest a small decline in length of stay, indicating some impact on the intensive margin of how sick individuals are when admitted. These estimates are available upon request.

4.1 Robustness Checks

I perform a series of robustness checks to validate the previous results. First, I estimate the impact of the law on unrelated causes in order to establish that there are no other underlying changes in supply or demand at SSA hospitals that would lead to the observed patterns for infections. These placebo tests are performed on admission rates due to cerebral infarctions and rates due to mental illness. The estimates for equation 1 are shown in columns 4-5 of Table 2. In both cases, the estimates are positive and statistically indistinguishable from zero. Figure 4 plots the coefficients from equation 2, showing no discernible pattern in these statistically insignificant coefficients.

Second, I explore alternative window sizes in the estimation of equation 1. These results are shown in columns 2-5 of Table 3, for a time window of 8, 10, 14 and 16 weeks, respectively. The estimates are similar to the baseline results in panels A, B and C, corresponding to all infections, bacterial and viral infections, respectively.

Third, column 6 of Table 3 includes the 2009 data. The estimates show that the main results are maintained. Lastly, to address the potential issue of having a large mass at zero in the dependent variable, column 7 presents the results from a left-censored Tobit model. Although the magnitude of the estimates is unusually large, the results are significant and in the same direction as the main findings, implying that these are not driven by the mass at zero.

5 Heterogeneous Effects

This section explores heterogeneous effects of the antibiotics law by age and by average education of the patients' municipality of residence. The former is motivated by the descriptive relationship between self-medication and age, and provides supporting evidence of the channels through which the law impacts hospitalization rates. The latter is motivated by the conceptual framework in terms of the tradeoff in choosing a course of action

when self-medication is no longer available, and suggests that OTC access regulations may have detrimental effects on the socioeconomic health gradient in contexts where access to affordable healthcare is lacking.

5.1 Differential Effects by Age

Figure 2 plots the smooth relationship between average reported self-medication and age, based on the 2006 ENSANUT. This descriptive exercise reveals that average self-medication rates increase with age, reaching a peak level at around 20 years old. After that point, there is a gradual decline in self-medication, with rates becoming relatively stable at age 65. A regulation that restricts OTC access to medications should more likely affect individuals that self-medicate at high rates.

To test this, I divide the population into four age groups: young children ages 0-4, older children ages 5-14, adults ages 15-64, and older adults ages 65 and over. These groups are based on trends and jumps in the scatterplot of Figure 2. I then follow the same estimation strategy as in the main findings for each group separately. Results are robust to alternative specifications of the age groups.

Table 4 presents the results from estimating equation 1 for the full sample (column 1) and for each age group (columns 2-5). In panel A (all infections), the coefficient on the interaction of the post August 25 indicator and the indicator for 2010 is negative for all four age groups, and significant in all cases except for older children. The magnitude is largest for adults (four times the size of the effect for older adults). Columns 2-5 effectively decompose the full effect of a 41% decline in admission rates due to infections into a 4, 2, 28, and 7% decline for each of the four age groups, respectively. The same pattern holds in panels B and C, with the majority of the effect in the full sample driven by adults ages 15-64.

Figure 5 plots the coefficients from estimating equation 2 separately for each age group, with admission rates due to infections as the dependent variable. Under this specification, the same patterns hold. Young children, older children and older adults do not seem to

experience any significant effects of the law, while the pattern for adults matches the main results in Figure 3a. Similar results are attained for viral admission rates, shown in Figure D1 in Appendix D.[18]

These results suggest that the improvements in health after the implementation of the law are driven almost entirely by adults, with very small impacts for other age groups. Only individuals who are more likely to self-medicate are actually affected by this regulation, as these individuals are now forced to consider seeking professional care since self-medication is no longer an option. This finding discards alternative interpretations of the main results, such as individuals modifying their behavior because the law makes health more salient, independently of self-medication behavior.

5.2 Differential Effects by Education

Based on the framework developed in Section 2, this section explores heterogeneous effects based on characteristics of the patients' municipality of residence. We expect that individuals with a higher opportunity cost of being sick are more likely to switch from self-medication to professional healthcare after the OTC access regulation. Hence, the improvements in health outcomes observed in the main findings should be driven by these patients.

Unfortunately, I do not observe any socioeconomic status characteristics for each patient in these data. However, I do observe the patients' municipality of residence. Around 40% of all patients are hospitalized at SSA hospitals in a municipality different from where they reside. In general, SSA affiliates are assigned either to the hospital in their own municipality, or to the closest one (note that not every municipality has an SSA hospital, although every municipality has at least one outpatient clinic).

As outlined above, using data from the 2010 census, I construct two schooling measures at the municipality level. I then classify municipalities into low or high education based

[18] In the case of bacterial admission rates, Figure 3b shows that there does not seem to be much of an effect for this type of infections. As such, decomposing the effect by age groups does not yield many insights. These results are available upon request.

on their position relative to the mean. This allows me to obtain separate admission rates for patients from low and high schooling municipalities. Note that this is independent of whether patients are hospitalized in their own municipality, although there is a substantial correlation between living in a higher education municipalities and receiving inpatient care in the same municipality.

Table 5 shows the results from estimating equation 1 for the full sample (column 1), and for patients from low and high schooling municipalities based on the no schooling measure (columns 2-3) and on the average years of schooling measure (columns 4-5). In panel A (all infections), the 41% decline found for the full sample is decomposed into a 13 and 27% decline for patients from low schooling and high schooling municipalities, respectively, as based on the no schooling measure. For the average years of schooling measure, the effects are a decrease of 17 and 23%. The same results hold for bacterial and viral infections in panels B and C.

Figure 6 plots the coefficients from equation 2 separately by education of the municipality of residence for each of the two schooling measures, taking admission rates due to all infections as the dependent variable. These results corroborate the previous findings, with the effect driven almost entirely by patients from high education municipalities. Figure D2 in Appendix D shows similar patterns for viral infections.

The findings in this section suggest that the law limiting OTC access to antibiotics resulted in differential responses based on socioeconomic status. Individuals from above average municipalities experienced significant reductions in admission rates, as their probability of switching from self-medication to professional care is higher. Those from below average municipalities were presumably less able to absorb the cost of professional healthcare, and hence did not experience a decline in admission rates. This insight is important as it shows that supply regulations in contexts without universal access to affordable healthcare may increase the socioeconomic health gradient, as only individuals from the right side of the distribution are able to switch to professional medical care.

6 Conclusion

This paper analyzes the consequences of a regulation restricting OTC access to antibiotics in Mexico on health outcomes, as measured by admission rates due to infections at public SSA hospitals. There are two main contributions to our understanding of the effects of supply-side interventions that curb self-medication. First, I show that infections for which there is a greater mismatch between self-treatment and treatment prescribed by a physician are the ones for which there is a greater improvement in health outcomes. This follows from the fact that individuals are worse at treating these diseases on their own.

The second contribution consists in showing that there may be unintended consequences when these types of regulations are introduced in contexts where access to affordable healthcare is lacking. The gains in health outcomes are experienced by patients from municipalities from the right side of the socioeconomic distribution. This implies that OTC restrictions may exacerbate the socioeconomic health gradient if they are unaccompanied by policies that expand access to affordable care.

It is important to note that this paper is unable to gauge effects on other measures of patient health, such as volume of outpatient visits and duration of sickness spells. Future work could explore this in order to fully understand the effects of OTC regulations on individuals' health outcomes. Furthermore, informing as to the extent of policies necessary to expand affordable healthcare for the segment of the population unable to switch from self-medication to medical care is also beyond the scope of this paper.

References

Adhvaryu, A. R. and A. Nyshadham (2012). Schooling, child labor, and the returns to healthcare in Tanzania. *Journal of Human Resources 47*(2), 364–396.

Agüero, J. and T. Beleche (2016). Health shocks and the long-lasting change in health behaviors: Evidence from Mexico. Technical report, University of Connecticut Working Papers 2016-26.

Andersson, D. I. and D. Hughes (2010). Antibiotic resistance and its cost: is it possible to reverse resistance? *Nature Reviews Microbiology 8*(4), 260–271.

Barnett, M. L. and J. A. Linder (2014a). Antibiotic prescribing for adults with acute bronchitis in the United States, 1996-2010. *JAMA 311*(19), 2020–2022.

Barnett, M. L. and J. A. Linder (2014b). Antibiotic prescribing to adults with sore throat in the United States, 1997-2010. *JAMA internal medicine 174*(1), 138–140.

Bennett, D., C.-L. Hung, and T.-L. Lauderdale (2010). Health care competition and antibiotic use in Taiwan. *Harris School of Policy Studies 8*.

Chang, F.-R. and P. Trivedi (2003). Economics of self-medication: theory and evidence. *Health economics 12*(9), 721–739.

Chopra, I. and M. Roberts (2001). Tetracycline antibiotics: mode of action, applications, molecular biology, and epidemiology of bacterial resistance. *Microbiology and molecular biology reviews 65*(2), 232–260.

Chowell, G., S. Echevarría-Zuno, C. Viboud, L. Simonsen, J. Tamerius, M. A. Miller, and V. H. Borja-Aburto (2011). Characterizing the epidemiology of the 2009 influenza A/H1N1 pandemic in Mexico. *PLoS medicine 8*(5), e1000436.

Currie, J., W. Lin, and W. Zhang (2011). Patient knowledge and antibiotic abuse: Evidence from an audit study in China. *Journal of Health Economics 30*(5), 933–949.

De Jaegher, K. and M. Jegers (2001). The physician–patient relationship as a game of strategic information transmission. *Health economics 10*(7), 651–668.

Domínguez-Cherit, G., S. E. Lapinsky, A. E. Macias, R. Pinto, L. Espinosa-Perez, A. de la Torre, M. Poblano-Morales, J. A. Baltazar-Torres, E. Bautista, A. Martinez, et al. (2009). Critically ill patients with 2009 influenza A(H1N) in Mexico. *Jama 302*(17), 1880–1887.

Dreser, A., E. Vázquez-Vélez, S. Treviño, and V. J. Wirtz (2012). Regulation of antibiotic sales in Mexico: An analysis of printed media coverage and stakeholder participation. *BMC Public Health 12*(1), 1051.

Dreser, A., V. J. Wirtz, K. K. Corbett, and G. Echániz (2008). Antibiotic use in Mexico: Review of problems and policies. *Salud Pública de México 50*, S480–S487.

Elizondo-Montemayor, L., M. M. Alvarez, M. Hernández-Torre, P. A. Ugalde-Casas, L. Lam-Franco, H. Bustamante-Careaga, F. Castilleja-Leal, J. Contreras-Castillo, H. Moreno-Sánchez, D. Tamargo-Barrera, et al. (2011). Seroprevalence of antibodies to influenza A/H1N1/2009 among transmission risk groups after the second wave in Mexico, by a virus-free ELISA method. *International Journal of Infectious Diseases 15*(11), e781–e786.

Fisher-Hoch, S. P. (2012). Missed opportunities for diagnosis and treatment of diabetes, hypertension, and hypercholesterolemia in a Mexican American population, Cameron County Hispanic Cohort, 2003–2008. *Preventing chronic disease 9*.

FUNSALUD (2014). Estudio sobre la práctica de la atención médica en consultorios médicos adyacentes a farmacias privadas. Technical report, Fundación Mexicana para la Salud, A.C.

Geoffard, P.-Y. and T. Philipson (1996). Rational epidemics and their public control. *International Economic Review*, 603–624.

Kremer, M. (1996). Integrating behavioral choice into epidemiological models of AIDS. *The Quarterly Journal of Economics 111*(2), 549–573.

Laxminarayan, R. and G. M. Brown (2001). Economics of antibiotic resistance: A theory of optimal use. *Journal of Environmental Economics and Management 42*(2), 183–206.

Neu, H. C. (1992). The crisis in antibiotic resistance. *Science 257*(5073), 1064–1074.

Okeke, I. N., A. Lamikanra, and R. Edelman (1999). Socioeconomic and behavioral factors leading to acquired bacterial resistance to antibiotics in developing countries. *Emerging infectious diseases 5*(1), 18.

Oster, E. (2012). HIV and sexual behavior change: Why not Africa? *Journal of Health Economics 31*(1), 35–49.

Pauly, M. V. and F. E. Blavin (2008). Moral hazard in insurance, value-based cost sharing, and the benefits of blissful ignorance. *Journal of Health Economics 27*(6), 1407–1417.

Pérez-Cuevas, R., S. V. Doubova, V. J. Wirtz, E. Servan-Mori, A. Dreser, and M. Hernández-Ávila (2014). Effects of the expansion of doctors offices adjacent to private pharmacies in Mexico: secondary data analysis of a national survey. *BMJ open 4*(5).

Pérez-Padilla, R., R. Fernández, C. García-Sancho, F. Franco-Marina, E. Mondragón, and P. Volkow (2011). Demand for care and nosocomial infection rate during the first influenza AH1N1 2009 virus outbreak at a referral hospital in Mexico City. *Salud pública de México 53*(4), 334–340.

Rodríguez-Noriega, E., G. León-Garnica, S. Petersen-Morfín, H. R. Pérez-Gómez, E. González-Díaz, and R. Morfín-Otero (2014). Evolution of bacterial resistance to antibiotics in Mexico, 1973-2013. *Biomédica 34*, 181–190.

Rubli, A. (2017). Low-cost, limited-service private healthcare providers: Evidence from Mexico. Technical report, Brown University.

Ruiz, M. E. (2010). Risks of self-medication practices. *Current drug safety 5*(4), 315–323.

Santa-Ana-Tellez, Y., A. K. Mantel-Teeuwisse, A. Dreser, H. G. Leufkens, and V. J. Wirtz (2013). Impact of over-the-counter restrictions on antibiotic consumption in Brazil and Mexico. *PloS one 8*(10), e75550.

Schottmüller, C. (2013). Cost incentives for doctors: A double-edged sword. *European Economic Review 61*, 43–58.

Schrag, S. J. and V. Perrot (1996). Reducing antibiotic resistance. *Nature 381*(6578), 120.

WHO (2002). Promoting rational use of medicines: core components. Technical report, World Health Organization.

WHO (2013). A global brief on hypertension: silent killer, global public health crisis. Technical report, World Health Organization.

Wirtz, V., J. Herrera-Patino, Y. Santa-Ana-Tellez, A. Dreser, M. Elseviers, and R. Van-der Stichele (2013). Analysing policy interventions to prohibit over-the-counter antibiotic sales in four Latin American countries. *Tropical Medicine & International Health 18*(6), 665–673.

Wirtz, V. J., A. Dreser, and R. Gonzales (2010). Trends in antibiotic utilization in eight Latin American countries, 1997-2007. *Revista Panamericana de Salud Pública 27*(3), 219–225.

Wirtz, V. J., A. Dreser, and J. Silva (2007). Patrones de prescripcion medica y de auto prescripcion de antibioticos en Morelos 2006. In . E. N. de Investigadores (Ed.), *Comision Coordinadora de Institutos Nacionales de Salud y Hospitales de Alta Especialidad*.

Wirtz, V. J., M. R. Reich, R. Leyva Flores, and A. Dreser (2008). Medicines in Mexico, 1990-2004: Systematic review of research on access and use. *Salud Pública de México 50*, S470–S479.

Wolff, M. J. (1993). Use and misuse of antibiotics in Latin America. *Clinical infectious diseases 17*(Supplement 2), S346–S351.

Table 1:
Summary Statistics

	Full sample	Ages 0-4	Ages 5-14	Ages 15-64	Ages 65+	No schooling measure		Years of schooling measure	
						Low	High	Low	High
Panel A: Individual Characteristics, 2006									
Fraction public insurance	0.463	0.407***	0.447***	0.463	0.580***	0.363	0.496***	0.372	0.499***
	(0.499)	(0.491)	(0.497)	(0.499)	(0.494)	(0.481)	(0.500)	(0.483)	(0.500)
Fraction private insurance	0.009	0.007***	0.008***	0.010	0.008**	0.002	0.012***	0.002	0.012***
	(0.096)	(0.086)	(0.087)	(0.101)	(0.088)	(0.044)	(0.107)	(0.043)	(0.110)
Fraction uninsured	0.528	0.586***	0.545***	0.526	0.413***	0.635	0.492***	0.626	0.489***
	(0.499)	(0.493)	(0.498)	(0.499)	(0.492)	(0.481)	(0.500)	(0.484)	(0.500)
Observations	206,155	19,603	47,977	124,977	13,598	49,455	156,700	61,982	144,173
Fraction self-medicates	0.404	0.283***	0.413***	0.450	0.299***	0.462	0.385***	0.432	0.394***
	(0.491)	(0.451)	(0.492)	(0.497)	(0.458)	(0.499)	(0.487)	(0.495)	(0.489)
Observations	22,561	3,259	4,512	12,289	2,501	5,278	17,283	6,394	16,167
Panel B: SSA Hospital Admission Rates, 2007-2014 weekly									
All infections	0.81	0.12***	0.18***	0.45	0.06***	0.29	0.52***	0.27	0.55***
	(3.55)	(1.04)	(1.19)	(2.41)	(0.69)	(2.23)	(2.51)	(1.97)	(2.63)
Bacterial infections	0.26	0.04***	0.05***	0.13	0.03***	0.10	0.15***	0.10	0.16***
	(1.62)	(0.53)	(0.60)	(1.11)	(0.50)	(1.17)	(1.08)	(1.12)	(1.10)
Viral infections	0.56	0.08***	0.12***	0.32	0.03***	0.19	0.37***	0.17	0.39***
	(2.98)	(0.84)	(0.97)	(2.07)	(0.45)	(1.79)	(2.16)	(1.53)	(2.27)
Observations	341,536	341,536	341,536	341,536	341,536	341,536	341,536	341,536	341,536

Notes: Means are reported with standard errors in parentheses. The first column shows statistics for the full sample, the next four columns divide the population by age, and the last four columns divide the population by municipality-level schooling measures. The first of these schooling measures classifies municipalities above and below the average fraction of the population ages 12 and over without schooling, while the second measure considers whether the municipality is above or below the average imputed years of schooling for individuals ages 12 and over. Both of these measures are based on the 2010 census. Difference in means tests are shown relative to individuals ages 15-64 and relative to low schooling. Panel A shows summary statistics taken from the 2006 ENSANUT, where the full survey sample is asked about insurance and only the subsample of individuals who report being sick in the past two weeks are asked about self-medication. Survey weights are used in calculations for Panel A. Panel B shows summary statistics for weekly SSA hospital admission rates per 100,000 individuals from 2007 to 2014.
*** p<0.01, ** p<0.05, * p<0.1

Table 2:
Effect of the Antibiotics Law on Hospital Admission Rates

	Admission Rates for Infections			Placebo Checks	
	All	Bacterial	Viral	Strokes	Mental
	(1)	(2)	(3)	(4)	(5)
Post Aug. 25 × 2010	-0.400***	-0.158***	-0.242***	0.006	0.147
	(0.1161)	(0.0576)	(0.0891)	(0.0086)	(0.1415)
Post Aug. 25	0.106	0.139***	-0.033	-0.009	-0.046
	(0.1043)	(0.0499)	(0.0828)	(0.0069)	(0.0957)
Test of sum of coefficients	-0.294***	-0.018	-0.276***	-0.003	0.101
	(0.0554)	(0.0197)	(0.0509)	(0.0042)	(0.0658)
Observations	143,675	143,675	143,675	143,675	143,675
R-squared	0.286	0.187	0.257	0.164	0.835
Mean dep. variable	0.986	0.272	0.714	0.029	0.638

Notes: This table shows the main results from estimating equation 1. The sample excludes 2009 due to the AH1N1 influenza epidemic, and restricts to 12 weeks on either side of August 25 for all years (25 weeks × 7 years × 821 hospitals). All regressions include hospital, week, and year fixed effects. Standard errors are clustered at the hospital level. The coefficient on the post August 25 indicator shows how rates compare before and after this date, for a given year. The coefficient on the indicator for post August 25 interacted with a 2010 indicator shows the additional effect in the year of the antibiotics law. A test for the sum of these coefficients is shown. This test indicates the total change from before to after August 25 in the year of the antibiotics law. Columns 1-3 show the effect on admission rates for infections, while columns 4-5 show placebo checks (effect on admission rates for cerebral infarction and for mental illness).
*** p<0.01, ** p<0.05, * p<0.1

Table 3:
Robustness Checks for the Main Results

		Different window sizes					
	Baseline	±8 weeks	±10 weeks	±14 weeks	±16 weeks	Incl. 2009	Tobit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All Infections							
Post Aug. 25 × 2010	-0.400***	-0.369***	-0.386***	-0.402***	-0.370***	-0.451***	-1.910***
	(0.1161)	(0.1290)	(0.1215)	(0.1092)	(0.1002)	(0.1169)	(0.4234)
Post Aug. 25	0.106	0.076	0.093	0.122	0.123	0.106	0.993***
	(0.1043)	(0.1185)	(0.1105)	(0.0991)	(0.0924)	(0.1043)	(0.3468)
Test of sum of coeffs.	-0.294***	-0.293***	-0.293***	-0.280***	-0.248***	-0.345***	-0.918***
	(0.0554)	(0.0624)	(0.0586)	(0.0518)	(0.0465)	(0.0580)	(0.2000)
R-squared	0.286	0.298	0.294	0.276	0.266	0.272	0.128
Mean dep. variable	0.986	1.053	1.019	0.952	0.909	1.001	0.986
Panel B: Bacterial Infections							
Post Aug. 25 × 2010	-0.158***	-0.167***	-0.149***	-0.156***	-0.146***	-0.159***	-1.066***
	(0.0576)	(0.0609)	(0.0564)	(0.0561)	(0.0535)	(0.0578)	(0.3228)
Post Aug. 25	0.139***	0.133**	0.126**	0.137***	0.134***	0.139***	0.891***
	(0.0499)	(0.0533)	(0.0498)	(0.0504)	(0.0497)	(0.0499)	(0.2599)
Test of sum of coeffs.	-0.018	-0.0338	-0.0222	-0.0195	-0.0121	-0.020	-0.175
	(0.0197)	(0.0237)	(0.0209)	(0.0198)	(0.0179)	(0.0195)	(0.1560)
R-squared	0.187	0.186	0.184	0.186	0.186	0.182	0.133
Mean dep. variable	0.272	0.274	0.270	0.271	0.266	0.272	0.272
Panel C: Viral Infections							
Post Aug. 25 × 2010	-0.242***	-0.203**	-0.237**	-0.245***	-0.224***	-0.292***	-1.712***
	(0.0891)	(0.1012)	(0.0954)	(0.0826)	(0.0748)	(0.0896)	(0.4471)
Post Aug. 25	-0.033	-0.057	-0.033	-0.015	-0.011	-0.033	0.651*
	(0.0828)	(0.0985)	(0.0908)	(0.0766)	(0.0699)	(0.0828)	(0.3580)
Test of sum of coeffs.	-0.276***	-0.260***	-0.271***	-0.260***	-0.235***	-0.325***	-1.061***
	(0.0509)	(0.0555)	(0.0530)	(0.0470)	(0.0427)	(0.0535)	(0.2400)
R-squared	0.257	0.276	0.270	0.243	0.228	0.241	0.146
Mean dep. variable	0.714	0.779	0.749	0.681	0.643	0.728	0.714
Observations	143,675	97,699	120,687	166,663	189,651	164,200	143,675

Notes: This table shows robustness checks for the main results from estimating equation 1. Panel A shows the results for all infections, Panel B restricts to bacterial infections, and Panel C to viral infections. All regressions include hospital, week, and year fixed effects. Standard errors are clustered at the hospital level. The coefficient on the post August 25 indicator shows how rates compare before and after this date, for a given year. The coefficient on the indicator for post August 25 interacted with a 2010 indicator shows the additional effect in the year of the antibiotics law. A test for the sum of these coefficients is shown. This test indicates the total change from before to after August 25 in the year of the antibiotics law. Column 1 shows the main baseline result. Columns 2-5 present different window sizes around August 25. Column 6 includes 2009 data. Column 7 shows the results from a left-censored Tobit specification (pseudo R-squared shown for this model).
*** p<0.01, ** p<0.05, * p<0.1

Table 4:
Heterogeneous Effects by Patients' Age

	Full sample (1)	Ages 0-4 (2)	Ages 5-14 (3)	Ages 15-64 (4)	Ages 65+ (5)
Panel A: All Infections					
Post Aug. 25 × 2010	-0.400***	-0.043***	-0.016	-0.276***	-0.065***
	(0.1161)	(0.0152)	(0.0292)	(0.0830)	(0.0162)
Post Aug. 25	0.106	0.019	-0.031	0.076	0.039***
	(0.1043)	(0.0119)	(0.0293)	(0.0680)	(0.0120)
Test of sum of coeffs.	-0.294***	-0.023**	-0.047**	-0.200***	-0.026**
	(0.0554)	(0.0093)	(0.0199)	(0.0410)	(0.0099)
R-squared	0.286	0.232	0.185	0.228	0.078
Panel B: Bacterial Infections					
Post Aug. 25 × 2010	-0.158***	-0.023***	-0.010	-0.097**	-0.029***
	(0.0576)	(0.0088)	(0.0128)	(0.0407)	(0.0108)
Post Aug. 25	0.139***	0.021***	0.021*	0.072**	0.025***
	(0.0499)	(0.0075)	(0.0112)	(0.0313)	(0.0088)
Test of sum of coeffs.	-0.018	-0.002	0.011	-0.025***	-0.004**
	(0.0197)	(0.0053)	(0.0075)	(0.0152)	(0.0073)
R-squared	0.187	0.077	0.063	0.134	0.074
Panel C: Viral Infections					
Post Aug. 25 × 2010	-0.242***	-0.020*	-0.006	-0.179***	-0.036***
	(0.0891)	(0.0111)	(0.0257)	(0.0630)	(0.0101)
Post Aug. 25	-0.033	-0.001	-0.052**	0.005	0.014**
	(0.0828)	(0.0095)	(0.0262)	(0.0535)	(0.0066)
Test of sum of coeffs.	-0.276***	-0.021**	-0.058***	-0.175***	-0.022***
	(0.0509)	(0.0086)	(0.0178)	(0.0363)	(0.0066)
R-squared	0.257	0.197	0.170	0.220	0.042
Observations	143,675	143,675	143,675	143,675	143,675

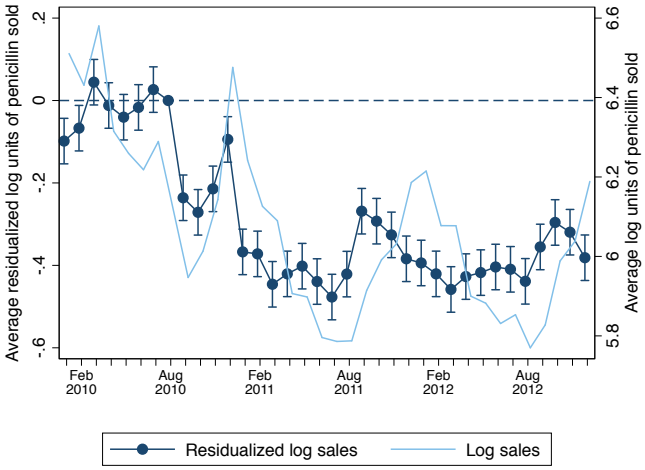
Notes: This table explores heterogeneous effects by dividing patients into age groups and estimating equation 1. Panel A shows the results for all infections, Panel B restricts to bacterial infections, and Panel C to viral infections. All regressions include hospital, week, and year fixed effects. Standard errors are clustered at the hospital level. The coefficient on the post August 25 indicator shows how rates compare before and after this date, for a given year. The coefficient on the indicator for post August 25 interacted with a 2010 indicator shows the additional effect in the year of the antibiotics law. A test for the sum of these coefficients is shown. This test indicates the total change from before to after August 25 in the year of the antibiotics law. Column 1 shows the main results for the full sample. Column 2 restricts to admission rates of individuals ages 0-4, column 2 shows ages 5-14, column 3 ages 15-64, and column 4 restricts to patients 65 and older. *** p<0.01, ** p<0.05, * p<0.1

Table 5:
Heterogeneous Effects by Average Education of Patients' Municipality of Residence

		No schooling measure		Years of schooling measure	
	Full sample	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A: All Infections					
Post Aug. 25 × 2010	-0.400***	-0.130*	-0.270***	-0.171***	-0.229***
	(0.1161)	(0.0766)	(0.0797)	(0.0659)	(0.0851)
Post Aug. 25	0.106	0.051	0.055	0.098	0.008
	(0.1043)	(0.0724)	(0.0684)	(0.0611)	(0.0746)
Test of sum of coeffs.	-0.294***	-0.079**	-0.215***	-0.073***	-0.221***
	(0.0554)	(0.0381)	(0.0350)	(0.0245)	(0.0424)
R-squared	0.286	0.257	0.263	0.215	0.266
Panel B: Bacterial Infections					
Post Aug. 25 × 2010	-0.158***	-0.053	-0.105**	-0.048	-0.110**
	(0.0576)	(0.0343)	(0.0436)	(0.0320)	(0.0454)
Post Aug. 25	0.139***	0.065**	0.074*	0.066**	0.074*
	(0.0499)	(0.0292)	(0.0398)	(0.0287)	(0.0399)
Test of sum of coeffs.	-0.018	0.013	-0.031**	0.018	-0.037**
	(0.0197)	(0.0137)	(0.0124)	(0.0125)	(0.0145)
R-squared	0.187	0.176	0.169	0.141	0.170
Panel C: Viral Infections					
Post Aug. 25 × 2010	-0.242***	-0.078	-0.165***	-0.123**	-0.119*
	(0.0891)	(0.0586)	(0.0614)	(0.0504)	(0.0658)
Post Aug. 25	-0.033	-0.014	-0.019	0.032	-0.065
	(0.0828)	(0.0601)	(0.0508)	(0.0458)	(0.0592)
Test of sum of coeffs.	-0.276***	-0.092**	-0.184***	-0.091***	-0.184***
	(0.0509)	(0.0360)	(0.0318)	(0.0233)	(0.0391)
R-squared	0.257	0.224	0.230	0.181	0.238
Observations	143,675	143,675	143,675	143,675	143,675

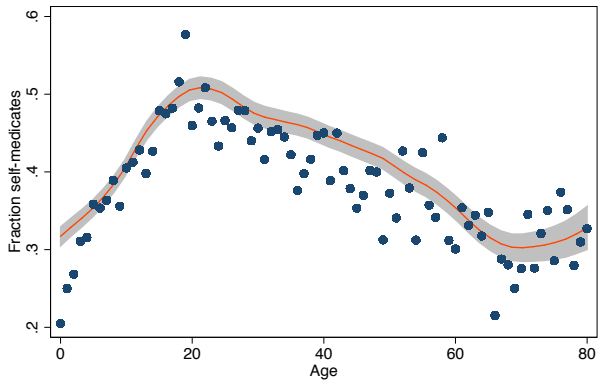
Notes: This table explores heterogeneous effects by dividing patients based on average education measures of their municipality of residence, and estimating equation 1. The no schooling measures considers whether the municipality of residence is above or below the average fraction of the population ages 12 and over without schooling. The years of schooling measure considers whether the municipality of residence is above or below the average imputed years of schooling for the population ages 12 and over. Panel A shows the results for all infections, Panel B restricts to bacterial infections, and Panel C to viral infections. All regressions include hospital, week, and year fixed effects. Standard errors are clustered at the hospital level. The coefficient on the post August 25 indicator shows how rates compare before and after this date, for a given year. The coefficient on the indicator for post August 25 interacted with a 2010 indicator shows the additional effect in the year of the antibiotics law. A test for the sum of these coefficients is shown. This test indicates the total change from before to after August 25 in the year of the antibiotics law. Column 1 shows the main results for the full sample. Columns 2-3 restrict to patients from low and high schooling municipalities respectively, based on the no schooling measure, while columns 4-5 do the same for the years of schooling measure.
*** p<0.01, ** p<0.05, * p<0.1

Figure 1:
Effect of Antibiotics Law on Sales of Penicillin



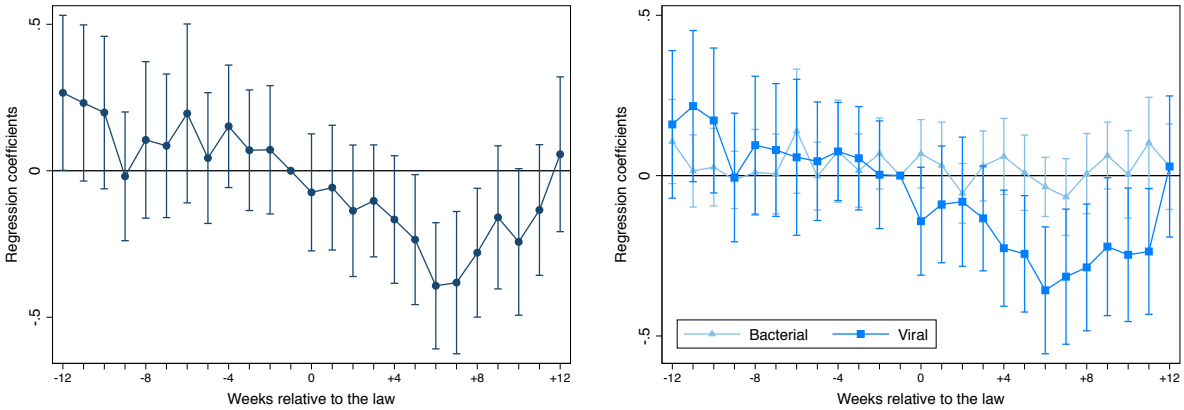
Notes: This figure shows the effect of the antibiotics law on nation-wide sales of penicillin. The sales data come from Knobloch Group, with monthly data from 2010-2012 for 672 urban markets. The solid light-colored line shows the log of the average volume sold by month in an urban market (technically, it is the log of units sold plus 0.01 to account for the 1% of urban market-months with zero units of penicillin sold in the private market). The graph also shows coefficients from a regression on residualized log sales. First, residuals are obtained from a regression of log sales on month indicators in order to account for within-year seasonality. Then I calculate a regression of these residuals on a vector of leads and lags of the month of the antibiotics law (August 2010) and urban market fixed effects, where the omitted category is August 2010.

Figure 2:
Relationship between Age and Self-Medication



Notes: The data for this plot come from the 2006 ENSANUT. This figure shows the relationship between the fraction that reports self-medicating during the last bout of illness in the two weeks prior to the survey and the respondents' age. The actual data points are shown in the scatterplot, while a kernel-weighted local polynomial smooth line is depicted with a 95% confidence interval. Individuals over the age of 80 are dropped from the sample, and survey weights are used.

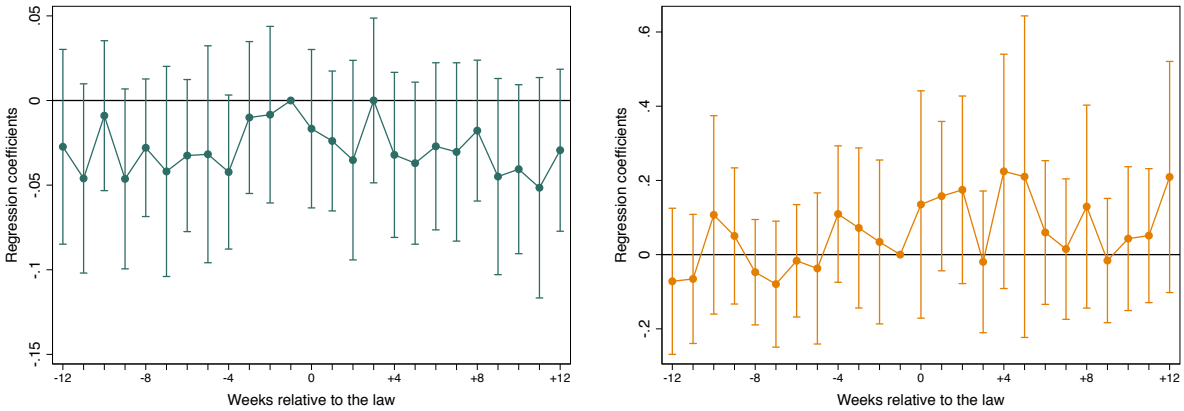
Figure 3:
Effect of Antibiotics Law on SSA Hospital Admission Rates due to Infections



(a) All infections (b) Types of infections

Notes: This figure shows the effect of the antibiotics law on admission rates per 100,000 due to infections. The graph on the left shows the effect on the rate for all infections, while the graph on the right shows the effect separately for infections due to bacteria and viruses. The figure plots the coefficients from a regression of rates on a vector of lead and lagged indicators for weeks relative to the antibiotics law, with the week prior to the law as the omitted category. The unit of observation for each regression is the hospital-week. Standard errors are clustered at the hospital level. Error bars show 95% confidence intervals. Each regression includes date fixed effects, hospital fixed effects, and two indicators for observations before and after 12 weeks of the antibiotics law. Data for 2009 are excluded. Estimates based on 298,844 observations. Means of the dependent variables are 0.80, 0.26, and 0.55 for all infections, bacteria, and viruses, respectively.

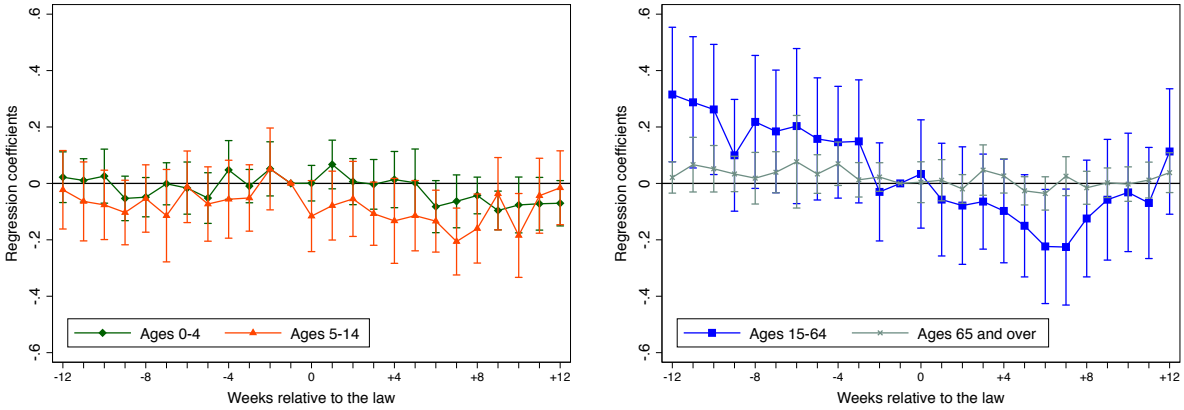
Figure 4:
Placebo Checks: Effect on SSA Hospital Admission Rates due to Unrelated Causes



(a) Cerebral infarction (b) Mental illness

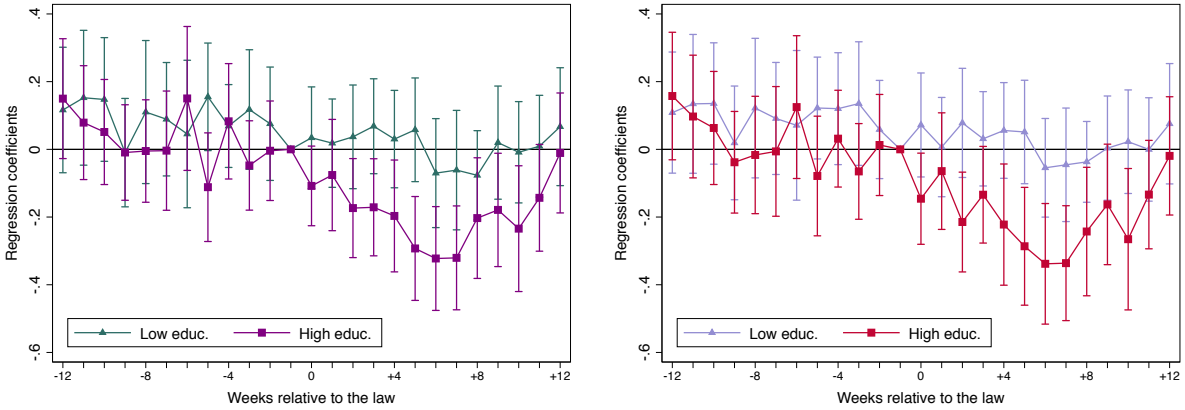
Notes: This figure shows a placebo exercise calculating the effect of the antibiotics law on admission rates per 100,000 due to causes unrelated with infections and antibiotics. The graph on the left shows the effect on the rate for admissions due to cerebral infarction, while the graph on the right shows the effect on the admission rate of mental illnesses. The figure plots the coefficients from a regression of rates on a vector of lead and lagged indicators for weeks relative to the antibiotics law, with the week prior to the law as the omitted category. The unit of observation for each regression is the hospital-week. Standard errors are clustered at the hospital level. Error bars show 95% confidence intervals. Each regression includes date fixed effects, hospital fixed effects, and two indicators for observations before and after 12 weeks of the antibiotics law. Data for 2009 are excluded. Estimates based on 298,844 observations. Means of the dependent variables are 0.03 and 0.66 for strokes and mental illnesses, respectively.

Figure 5:
Effect of Antibiotics Law on SSA Hospital Admission Rates due to Infections by Age Groups



Notes: This figure shows the effect of the antibiotics law on admission rates per 100,000 due to infections by different age groups. The graph on the left shows the effect on younger patients, while the graph on the right shows the effect on older patients. The figure plots the coefficients from a regression of rates on a vector of lead and lagged indicators for weeks relative to the antibiotics law, with the week prior to the law as the omitted category. The unit of observation for each regression is the hospital-week. Standard errors are clustered at the hospital level. Error bars show 95% confidence intervals. Each regression includes date fixed effects, hospital fixed effects, and two indicators for observations before and after 12 weeks of the antibiotics law. Data for 2009 are excluded. Estimates based on 298,844 observations.

Figure 6:
Effect of Antibiotics Law on SSA Hospital Admission Rates due to Infections by Average Education of Municipality of Residence



(a) No schooling measure

(b) Years of schooling measure

Notes: This figure shows the effect of the antibiotics law on admission rates per 100,000 due to infections by education levels of the patients' municipality of residence. The graph on the left calculates rates separately for patients from low versus high education municipalities, as based on the no schooling measure (above or below the average fraction of the population ages 12 and over without schooling). The graph on the right repeats the exercise for the years of schooling measure (above or below the average imputed years of schooling for the population ages 12 and over). The figure plots the coefficients from a regression of rates on a vector of lead and lagged indicators for weeks relative to the antibiotics law, with the week prior to the law as the omitted category. The unit of observation for each regression is the hospital-week. Standard errors are clustered at the hospital level. Error bars show 95% confidence intervals. Each regression includes date fixed effects, hospital fixed effects, and two indicators for observations before and after 12 weeks of the antibiotics law. Data for 2009 are excluded. Estimates based on 298,844 observations.

Appendices for Online Publication

A Healthcare in Mexico

Healthcare in Mexico is provided by both a public and private sector. The public sector is divided into separate institutions, with their own providers, hospitals, clinics and benefit plans. Formal workers are enrolled in the Mexican Social Security Institute (*Instituto Mexicano del Seguro Social*, IMSS). Workers in the informal economy, self-employed, and unemployed individuals have access to healthcare through the Department of Health (*Secretaria de Salud*, SSA), mainly through enrollment in a program called *Seguro Popular* (SP). State workers are enrolled in the Institute of Social Security and Services of State Workers (*Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado*, ISSSTE). Lastly, separate institutions exist for workers of the national oil company (Pemex), the Department of Defense, and the Marines. Health providers for the public system are the hospitals, clinics, and doctors that belong to these institutions, financed by a mix of contributions from the government, employers, and workers.

Private healthcare corresponds to private hospitals and clinics, and doctors working in a private practice. Employees at high wage levels often receive private insurance on top of the mandatory enrollment in IMSS. Note that private insurance is only valid with private providers.

According to the 2006 ENSANUT, 46% of the population was enrolled in one of the public healthcare institutions, 1% were covered by private insurance, and 53% of the population was uninsured. All uninsured individuals are eligible for enrollment in SP and the corresponding care at SSA clinics and hospitals. On the spot enrollment in SP is possible, and there is a small fee based on income levels, which explains why so many individuals remain uninsured.

Health service usage varies considerably relative to coverage, especially in terms of the private sector. According to the 2006 ENSANUT, 61% of all outpatient use occurs at public

clinics (of which 27% is at SSA clinics) while 39% is at private doctors' offices. Given the extremely low private insurance rates, this must all be payed out-of-pocket (OOP). On average, individuals payed 189 pesos per outpatient visit in 2006 (1 USD=11 pesos). The average cost at a public clinic was 39 pesos, and the average cost of private doctor visits was 465 pesos.

In terms of prescriptions, the public system provides drugs through their own pharmacies at outpatient clinics and hospitals. However, supply shortages and long waiting times imply that most medicines are bought OOP. According to the 2006 ENSANUT, 19% of individuals who visited a public outpatient clinic purchased their prescriptions at a private pharmacy.

Lastly, usage patterns of inpatient care also show a relatively large portion of the population choosing private hospitals, although at a lower percentage than outpatient care. The 2006 ENSANUT reveals that 79% of hospitalizations occur at a public hospital, of which about 29% is at an SSA hospital, and the rest at other public hospitals.

B Classification of Hospitalizations by Infection

The classification of diagnoses are based on the code assigned by SSA physicians and recorded in the data. These codes correspond to the International Statistical Classification of Diseases and Related Health Problems (ICD-10). Tables B1 and B2 show the diagnoses classified into bacterial and viral infections, respectively.

Table B1: Classification of Hospitalizations due to Bacteria

ICD-10 Code	Description of Diagnosis
A00-A05	Intestinal diseases: cholera, typhoid fever, salmonella, shigellosis, other bacterial intestinal infections, other bacterial food-borne intoxications
A15	Respiratory tuberculosis (bacteriologically and histologically confirmed)
A17-A19	Tuberculosis of the nervous system, tuberculosis of other organs, military tuberculosis
A50-A58	Congenital syphilis, early syphilis, late syphilis, other and unspecified syphilis, gonococcal infection (gonorrhea), chlamydial lymphogranuloma, other sexually transmitted chlamydial diseases, chancroid, granuloma inguinale
A65-A69	Non-venereal syphilis, yaws (spirochete bacterium Treponema pallidum pertenue), pinta (spirochete bacterium Treponema pallidum carateum), relapsing fever (Rickettsia and Borrelia bacteria), other spirochaetal infections
A70-A74	Clamydia psittaci infection, trachoma (bacterium Chlamydia trachomatis), other diseases caused by chlamydiae
A75-A79	Typhus fever, spotted fever (Rickettsia bacteria), Q fever (bacterium Coxiella burnetii), other rickettsioses
G00-G01	Bacterial meningitis, meningitis in bacterial diseases classified elsewhere
H00	Stye/Hordeolum and chalazion (bacterium Staphylococcus aureus)
J13-J15	Pneumonia due to Streptococcus pneumoniae, pneumonia due to Haemophilus influenzae, bacterial pneumonia not classified elsewhere
L00-L01	Staphylococcal scalded skin syndrome, impetigo (bacterium Staphylococcus aureus and sometimes Streptococcus pyogenes)
N30	Cystitis (bacterium Escherichia coli; in some rare cases, the cause may be other bacteria, viruses or fungi)

Table B2: Classification of Hospitalizations due to Viruses

ICD-10 Code	Description of Diagnosis
A08	Viral intestinal infections
A60	Anogenital herpes viral infection (herpes simplex)
A80-A89	Viral infections of the central nervous system: acute poliomyelitis, atypical virus infections of central nervous system, rabies, viral encephalitits, viral meningitis, other viral infections not specified elsewhere, unspecified viral infection of central nervous system
A90-A99	Arthropod-borne viral fevers and viral hemorrhagic fevers: dengue fever, dengue hemorrhagic fever, other mosquito and arthropod-borne viral fevers, yellow fever, arenaviral hemorrhagic fever, other viral hemorrhagic fevers
B00-B09	Viral infections characterized by skin and mucous membrane lesions: herpes viral infections (herpes simplex), varicella (chickenpox), zoster (herpes zoster), smallpox, monkeypox, measles, rubella (German measles), viral warts, other viral infections
B15-B19	Viral hepatitis: acute hepatitis A, acute hepatitis B, other acute viral hepatitis (hepatitis C and E), chronic viral hepatitis, unspecified viral hepatitis
B20-B24	Human immunodeficiency virus (HIV) disease: HIV disease resulting in infectious and parasitic diseases, HIV resulting in malignant neoplasms, HIV resulting in other specified diseases, HIV resulting in other conditions
B25-B34	Other viral diseases: cytomegaloviral disease, mumps, infectious mononucleosis, viral conjunctivitis, other viral diseases, viral infection of unspecified site
J00	Acute nasopharyngitis (common cold due mostly to the rhinovirus, and other viruses)
J09-J12	Influenza due to identified avian influenza virus, influenza due to identified influenza virus, influenza with virus not identified, viral pneumonia

C A Simple Model

An individual is observed in two time periods. In the first period, she presents a series of symptoms that are commonly associated with some sort of infection, but are not an indication of a serious, life-threatening condition. The individual must choose which action to take given these symptoms. In the second period, the bout of illness is either resolved and health is restored, or she is still sick and would require inpatient care.[1]

An individual's choice set in the first period is given by: seek professional medical care D, self-medicate S, and let the disease run its course by doing nothing N. The tradeoffs between these choices lie in the probabilities of restoring health and the costs of each option. There is a medically wrong treatment and a medically correct one. Define the following conditional probabilities:

$$\begin{aligned}
\pi_D &\equiv \Pr\left(\text{correct treatment} \mid D\right) \\
\pi_S &\equiv \Pr\left(\text{correct treatment} \mid S\right) \\
\phi_0 &\equiv \Pr\left(\text{restoring health} \mid \text{wrong treatment}\right) \\
\phi_1 &\equiv \Pr\left(\text{restoring health} \mid \text{correct treatment}\right)
\end{aligned}$$

The first two measure differences in diagnosis skills for doctors and individuals. This difference is exacerbated by information asymmetries between doctors and patients, knowledge stocks in terms of both medical knowledge and past experience, and possibly random noise. Assume naturally that:

$$\pi_D > \pi_S \qquad \text{(Assumption 1)}$$

On the other hand, ϕ_0 and ϕ_1 are measures of the expected outcome as a consequence of whether the treatment following from a diagnosis was correct or not. By construction, $\phi_1 > \phi_0$.

[1] This is a strong assumption, but can be relaxed to the individual having some positive probability of requiring inpatient care, and some positive probability of simply having to revisit her choice.

Let $\Delta\phi = \phi_1 - \phi_0$. Therefore, the probabilities of restoring health conditional on each choice are:

$$\begin{aligned}
\Pr\left(\text{restoring health} \mid D\right) &= \phi_0 + \pi_D \Delta\phi \\
\Pr\left(\text{restoring health} \mid S\right) &= \phi_0 + \pi_S \Delta\phi \\
\Pr\left(\text{restoring health} \mid N\right) &= \phi_0
\end{aligned}$$

There is a baseline probability ϕ_0 of getting better, which can be improved upon by diagnosis skills weighted by the relative efficiency of the correct treatment.

Individuals obtain a payoff of $y \geq 0$ in period two if health is restored, and a payoff normalized to zero otherwise. This payoff y does not necessarily imply income, and should instead be thought of as earnings potential or the opportunity cost of being sick. This underlying dimension is approximated in the empirics through average education of the municipality of residence.

There is a cost of going to the doctor given by C and a cost of self-medicating given by M. The cost of the doctor is both medicines and the actual consultation, while self-medication is just the latter, so that $C > M$. The same holds if we factor in time costs.

In period two, the expected utilities conditional on each choice are:

$$\begin{aligned}
U_D &= \left[\phi_0 + \pi_D \Delta\phi\right] y - C \\
U_S &= \left[\phi_0 + \pi_S \Delta\phi\right] y - M \\
U_N &= \phi_0 y
\end{aligned}$$

Let $\Delta\pi = \pi_D - \pi_S$. Given these payoffs, individuals will choose to self-medicate as long as it is better than going to the doctor and better than doing nothing, or if the following holds:

$$y < \frac{C - M}{\Delta\pi\Delta\phi} \tag{C1}$$

Under assumption 1, this fraction is a positive number.

Likewise, individuals will prefer to self-medicate over doing nothing if:

$$y > \frac{M}{\pi_S \Delta\phi} \tag{C2}$$

Joining equations C1 and C2 gives the condition that leads to individuals choosing self-medication. However, if $\frac{C-M}{\Delta\pi\Delta\phi} < \frac{M}{\pi_S\Delta\phi}$ the condition would never be met and no one self-medicates. Therefore, in order to observe self-medication, the following assumption must be made:

$$\frac{M}{C} < \frac{\pi_S}{\pi_D} \tag{Assumption 2}$$

Hence, as long as the relative cost of self-medicating with respect to going to the doctor is smaller than the relative benefit in diagnostic abilities of the individual with respect to the doctor, we will observe some self-medication.

Individuals will prefer to go to the doctor over nothing if:

$$y > \frac{C}{\pi_D \Delta\phi} \tag{C3}$$

Note that under Assumption 1 and Assumption 2, the following relationship holds:

$$\frac{M}{\pi_S\Delta\phi} < \frac{C}{\pi_D\Delta\phi} < \frac{C-M}{\Delta\pi\Delta\phi}$$

Suppose that the distribution of y over the range $[0, \bar{y}]$ has a cumulative distribution function given by the absolutely continuous function $F(\cdot)$. For convenience, define the following:

$$P \equiv \frac{M}{\pi_S\Delta\phi} \quad , \quad Q \equiv \frac{C}{\pi_D\Delta\phi} \quad , \quad R \equiv \frac{C-M}{\Delta\pi\Delta\phi}$$

Thus, the fraction of the population that self-medicates is given by $F(R) - F(P)$, the fraction that goes to the doctor is $1 - F(R)$, and the remaining fraction $F(P)$ chooses to do

nothing. Note that these proportions depend on the distribution of y and on the gap between P and R. This gap is larger whenever the relative marginal benefit is much larger than the relative marginal cost of self-medication with respect to formal healthcare (Assumption 2 holds more strongly), individuals are bad at diagnosing (smaller π_S), individuals are relatively bad at diagnosing (smaller $\Delta\pi$), and the right treatment is not very effective (smaller $\Delta\phi$).[2]

A regulation reducing OTC access eliminates the possibility of self-medication from the choice set. Under independence of irrelevant alternatives, the only change should occur for those self-medicating before.[3] This simply implies that individuals with $y > Q$ will choose to go to the doctor, while the rest do nothing. It is essential to note that the self-medicating population that now chooses professional care does so because they can afford it (their y is large enough). As such, the net effect of the law is ambiguous, both in terms of healthcare choices and potential consequences on health from these new choices.

As a mere illustration of the ambiguity of this first result, Figure C1 presents two different distributions of earnings potential y. The mass of the shaded gray areas is the fraction of the population that self-medicates before the regulation. For individuals in the lighter gray area, once self-medication is eliminated as an option, they prefer to do nothing, while those in the darker gray area will choose to go to the doctor. In the top graph, a higher fraction of individuals that self-medicated ends up choosing professional medical care, while the opposite happens in the bottom graph.

Now define a measure of welfare as the proportion of the population that recovers from the illness in the second period. Note that I am not defining welfare in terms of utility (which is decreasing for the mass of individuals who used to self-medicate). Instead, I consider welfare

[2]The size of the gap is:

$$P - R = \frac{\pi_S C - \pi_D M}{\pi_S \Delta\pi \Delta\phi}$$

[3]The axiom of independence of irrelevant alternatives need not hold in this situation. A strict regulation on antibiotic sales may explicitly or implicitly provide the population with additional information. This model abstracts from this.

from a social planner's perspective, where the relevant measure is the change in the amount of individuals who are regaining their health in the model's second period.

Let ΔW represent the net effect of OTC access regulations on welfare, measured as the fraction of the population whose health is restored in period two after the regulation minus the fraction recovering before:

$$\Delta W = \Delta\pi\Delta\phi[F(R) - F(Q)] - \pi_S\Delta\phi[F(Q) - F(P)] \tag{C4}$$

The first term in equation C4 quantifies the impact for the fraction that self-medicated before but are now choosing to go to the doctor, with the respective increase in the probability of getting better. Note that this term is always positive. The second term corresponds to those who choose to do nothing after the regulation is implemented. In this case, the effect is necessarily negative, as the probability of recovering is smaller.

Therefore, the regulation will increase welfare only if the first term in equation C4 is larger than the second. This result follows from the ambiguity in the segment of the population switching from self-medication to formal healthcare. This result will depend on the distribution of y, and on $\Delta\pi$.

I have assumed throughout that the entire population faces the same probabilities π_D, π_S, ϕ_1 and ϕ_0. This may not necessarily be the case. Assuming some distribution of these probabilities in the population adds a layer of complexity to the main results of this model. However, the ambiguity of the net effect of the regulation remains unchanged.

Extension to Different Illnesses

The model can be extended to consider two types of infections, which differ only in individual diagnosis skills π_S. Let a and b denote these infections, and define ρ as the known probability of being sick with infection a conditional on feeling sick. In other words, ρ is the prevalence

of infection type a in the population. Assume without loss of generality that:

$$\pi_S^a > \pi_S^b \tag{Assumption 3}$$

Therefore, infection a only differs from b in the probability that an individual that self-medicates will choose the right treatment. For example, if a denotes bacterial respiratory infections and b viral ones, then as long as individuals always decide to treat with antibiotics, the probability of assigning the right treatment will be larger for type a infections than for type b infections.[4]

Note that individuals do not know ex-ante whether they are infected with a or b. In fact, this uncertainty may never be resolved. In terms of the model, individuals only know that they are better at diagnosing one type of infection over the other, and the prevalence of each infection type. In period one, they decide between D, S and N as before. In period two, they only observe if the bout of illness is resolved or not.

Therefore, individuals cannot make different choices depending on whether they are sick with infection type a or b. They must consider their differential skills at diagnosis and the natural probability of occurrence of each infection type in order to decide the type of healthcare they get. On average, individuals know that their diagnosis skills are given by:

$$\Pi_S \equiv \rho\pi_S^a + (1-\rho)\pi_S^b$$

Proceeding as above, conditional on self-medication, the new probability of restoring health is given by:

$$\Pr\left(\text{restoring health} \mid S\right) = \phi_0 + \Pi_S \Delta\phi$$

[4]Empirical evidence on respiratory ailments in the US supports this characterization. Barnett and Linder (2014a) shows that the rate of prescriptions for antibiotics for acute bronchitis were around 71% in 2010, although the scientific evidence shows they should be zero for this disease. Additionally, antibiotic prescribing rates for sore throats caused by group A streptococcus are around 70%, although the prevalence of this bacterium is just 10%, according to Barnett and Linder (2014b).

with the corresponding expected payoff $[\phi_0 + \Pi_S \Delta\phi]\, y - M$. In order to guarantee that at least some individuals will prefer to self-medicate, Assumption 2 must be modified:

$$\frac{M}{C} < \frac{\Pi_S}{\pi_D} \qquad \text{(Assumption 2')}$$

The cutoff values of y for each choice are similarly given by:

$$P' \equiv \frac{M}{\Pi_S \Delta\phi} \quad , \quad Q' \equiv \frac{C}{\pi_D \Delta\phi} \quad , \quad R' \equiv \frac{C - M}{\Delta\Pi \Delta\phi}$$

where $\Delta\Pi = \pi_D - \Pi_S$. Note that $Q = Q'$, since the tradeoff between doing nothing and seeing a physician is unchanged. Intuitively, as Π_S gets larger, there will be a higher proportion of individuals choosing self-medication, since own diagnostic skills are improving. Fixing π_S^b, it can be shown that the derivative of P' with respect to the difference between π_S^a and π_S^b and with respect to ρ are both negative, while the same derivatives are positive for R', thus indicating a larger proportion of individuals choosing self-medication.

Now consider the change in welfare for each type of disease. Here, since welfare is defined through the probability of recovering, the uncertainty regarding the type of infection has been resolved ex-post (choices ex-ante are still in terms of the expectations). Following equation C4:

$$\Delta W_j = (\pi_D - \pi_S^j)\Delta\phi[F(R) - F(Q)] - \pi_S^j \Delta\phi[F(Q) - F(P)], \quad j \in \{a, b\} \qquad \text{(C5)}$$

As before, the distribution of y and the relative diagnosis skills between doctors and individuals will determine whether this effect is positive or negative.

The final intuition to be gained from this extension is how these welfare effects differ between the two types of illness. Calculating the difference between the changes in welfare:

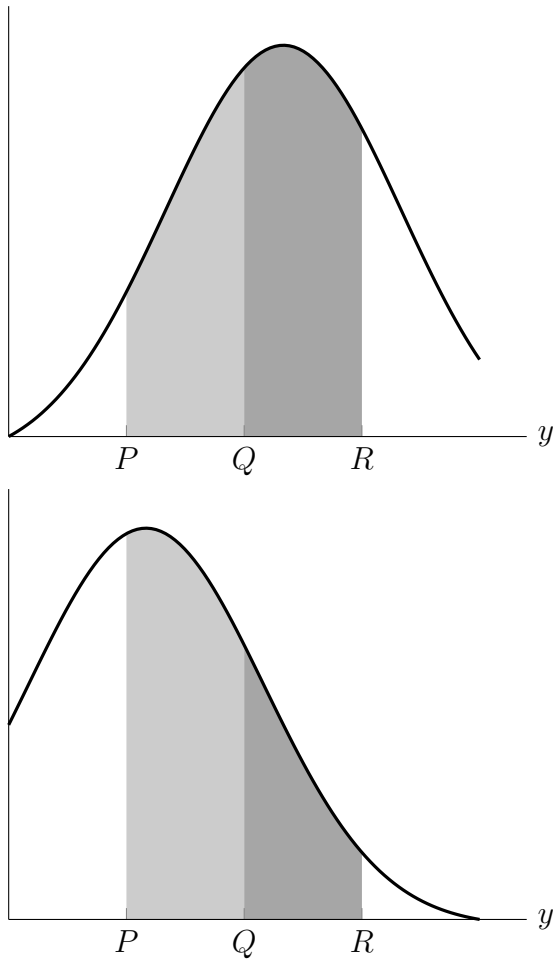
$$\Delta W_a - \Delta W_b = -(\pi_S^a - \pi_S^b)\Delta\phi[F(R) - F(P)] < 0 \qquad \text{(C6)}$$

Note that this holds under Assumption 3, such that individuals are better at self-medicating for infection a versus b. The last term indicates that this difference depends on the actual fraction of the population that self-medicated before the regulation, the middle term simply weights the difference by the relative effectiveness of the right treatment, and the first term refers to the difference in individuals' diagnosis skills for each infection type.

Also note that given the ambiguity result in the net effect, ΔW_a and ΔW_b can be either positive, negative or zero. If $\Delta W_a < 0$, then equation C6 holds regardless of the sign of ΔW_b. However, if both are negative, then there must be a larger loss in terms of type a infections than type b. If $\Delta W_a = 0$, then it must be that $\Delta W_b > 0$. Lastly, if $\Delta W_a > 0$, then equation C6 only holds if $\Delta W_b > 0$ and is larger in magnitude than the net effect on infection type a.

The result that the effects on type b infections should be larger simply follows from the fact that there is more to gain (or less to lose) by switching from self-medication to formal healthcare when individuals were infected with b, since they are worse at choosing the right treatment for those cases. In the two extremes, if the regulation is detrimental for both types of infection, it will be more so for the type that individuals were better at treating, and if the law is beneficial for both, it will improve outcomes more for the type that had more room for improvement.

Figure C1:
Outcome Examples of the Model



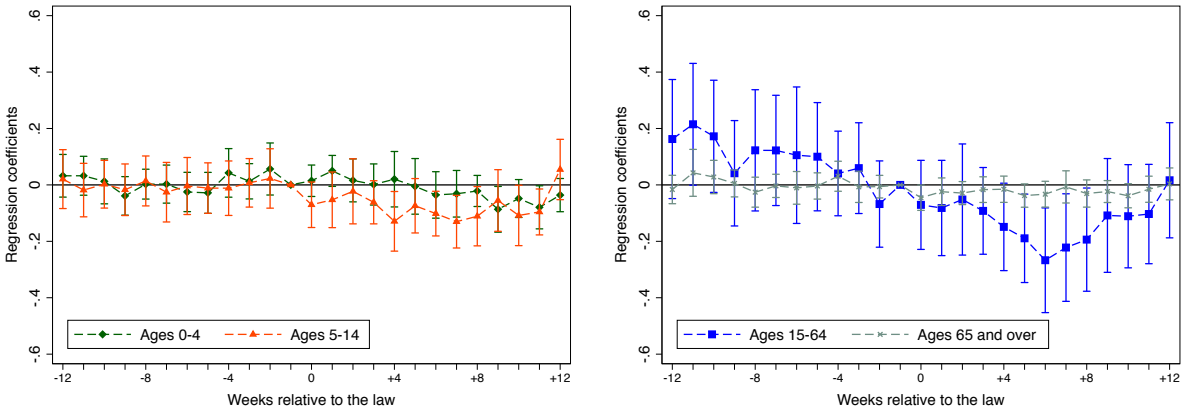
Notes: This figure shows two examples of the model based on different distributions of the opportunity cost of being sick y. The solid black line is the cumulative distribution function of y. The cutoff values P, Q, R are the same in both examples. The white area under the curve to the left of P is the proportion of individuals who always choose to do nothing. The white area to the right of R is the proportion that always chooses professional medical care. The shaded area between P and R represents individuals who self-medicate. Once a regulation is introduced that prevents self-medication, the individuals in the light gray area will switch to doing nothing, while individuals in the darker gray area shift towards professional medical care. The top figure shows a situation in which the proportion switching towards professional healthcare is larger, resulting in a net welfare increase. The bottom figure shows the opposite result.

D Additional Results

Figures D1 and D2 plot the coefficient estimates from equation 2, using viral admission rates as the dependent variable and dividing by age groups and by education of the municipality of residence, respectively. These results accompany Figures 5 and 6 in the paper.

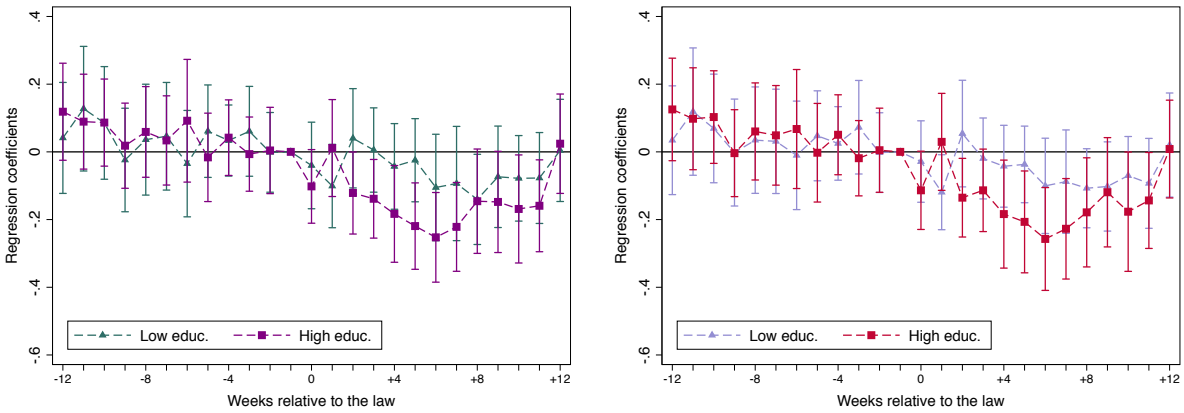
Figure D1 shows that the main result found for viral admission rates is driven almost entirely by adults ages 15-64. Figure D2 shows that patients from municipalities with above average levels of education are the ones that experience the decline in admission rates after the law is implemented. These results are consistent with the main findings for all infections.

Figure D1:
Effect of Antibiotics Law on SSA Hospital Admission Rates due to Viral Infections by Age Groups



Notes: This figure shows the effect of the antibiotics law on admission rates per 100,000 due to viral infections by different age groups. It plots the coefficients from a regression of rates on a vector of lead and lagged indicators for weeks relative to the antibiotics law, with the week prior to the law as the omitted category. The unit of observation for each regression is the hospital-week. Standard errors are clustered at the hospital level. Error bars show 95% confidence intervals. Each regression includes date fixed effects, hospital fixed effects, and two indicators for observations before and after 12 weeks of the antibiotics law. Data for 2009 are excluded. The graph on the left shows the effect on younger patients, while the graph on the right shows the effect on older patients.

Figure D2:
Effect of Antibiotics Law on SSA Hospital Admission Rates due to Viral Infections by Average Education of Municipality of Residence



(a) No schooling measure

(b) Years of schooling measure

Notes: This figure shows the effect of the antibiotics law on admission rates per 100,000 due to viral infections by education levels of the patients' municipality of residence. It plots the coefficients from a regression of rates on a vector of lead and lagged indicators for weeks relative to the antibiotics law, with the week prior to the law as the omitted category. The unit of observation for each regression is the hospital-week. Standard errors are clustered at the hospital level. Error bars show 95% confidence intervals. Each regression includes date fixed effects, hospital fixed effects, and two indicators for observations before and after 12 weeks of the antibiotics law. Data for 2009 are excluded. The graph on the left calculates rates separately for patients from low versus high education municipalities, as based on the no schooling measure (above or below the average fraction of the population ages 12 and over without schooling). The graph on the right repeats the exercise for the years of schooling measure (above or below the average imputed years of schooling for the population ages 12 and over).