Trade-Offs Between Access and Quality in Healthcare: Evidence from Retail Clinics in Mexico*

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Private market innovations may be an efficient solution to healthcare provision challenges in developing countries. This paper exploits the expansion of retail clinics at private pharmacies in Mexico to analyze changes in provider choices and to characterize quality in terms of prescriptions. I find that the first retail clinic entry in the vicinity of a public clinic leads to a 6% decline in public use, no evidence of new doctor visits, and a large shift toward stronger antibiotics in private-market sales. This suggests that retail clinic expansion shuffled patients away from existing providers toward doctors with stronger incentives to over-prescribe.

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Primary healthcare provision in the developing world still poses a significant challenge. Supply-side issues in access and quality exacerbate the prevalence of infectious diseases and the burden of chronic conditions (Das and Hammer, 2014; Dupas, 2011). Researchers have documented the many problems that arise from the public system in these settings, as well as multiple cost and quality concerns related to healthcare providers in the private market (Gertler, 1998; Dupas and Miguel, 2017; Dizon-Ross et al., 2015).[1]

Market innovations in healthcare delivery may be an efficient solution to healthcare provision in developing countries. These innovations, usually in the form of low-cost, limited-service private providers, such as retail clinics and mobile clinics, present an option that is cheaper than existing private doctors and quicker than seeking care at public clinics.[2] These alternatives are often cost-effective, especially when exploiting existing private networks such as retail-sector drug stores (Cohen et al., 2015).[3]

However, not much is known about how individuals change their healthcare provider decisions with the introduction of these alternatives, and hence to what extent agency problems may be an issue. Private market innovations may not necessarily lead to increased access if they only attract patients from existing providers. Furthermore, these new providers may trade off quality for lower prices and quicker service, especially in settings where low state capacity hinders regulatory efforts. The tension between the potential additional effort exerted by these new providers relative to existing ones and the inherent market incentives to over-treat may result in lower quality of care (Das et al., 2016).

[1]Publicly-provided care is generally not universal; low cost in terms of price, although costly in other aspects such as waiting times; and lower quality on some dimensions due to low-powered incentives, although there is considerable variation (Gertler, 1998; Das et al., 2016). Private health services have lower waiting times, but are more expensive and usually paid for out-of-pocket due to low private insurance rates (Leive and Xu, 2008). Lax regulations in these settings of low state capacity do not guarantee higher quality of private providers (Das et al., 2016).

[2]Innovations may also take the form of targeted, market-based incentives to channel patients to appropriate medical care and to bolster the diffusion of health information among members of a community (Björkman Nyqvist et al., 2017; Goldberg et al., 2018).

[3]Individuals are very sensitive to the price of diagnoses, but price inelastic to treatment (Dupas, 2011). Hence, markets that have evolved around the latter may serve to develop the former. Similarly, infrastructure networks, such as railroads, may decrease the cost of accessing certain communities (see for example the "Tren de la Salud" program in Mexico, https://www.fundaciongrupomexico.org/programas/Paginas/RutasDrVagon.aspx, accessed November 2018).

This paper analyzes these trade-offs between access and quality when introducing new types of private-market healthcare providers, by focusing on the expansion of private pharmacy-adjacent doctors' offices (PADOs) – essentially, retail clinics at private pharmacies – in Mexico. First, I analyze the effect of PADO entry on healthcare utilization, determining substitution patterns and identifying new doctor visits. Second, I analyze prescription patterns of antibiotics in order to characterize misaligned incentives at these new retail clinics.

The literature on alternative healthcare delivery in developing countries highlights the positive effects of innovations in expanding access in rural areas (Grabbe et al., 2010; Geoffroy et al., 2014) and boosting the use of diagnosis tools (Cohen et al., 2015), while criticizing misaligned financial incentives and lower quality (Björkman Nyqvist et al., 2018; Ross-Degnan et al., 1996; Tomson and Sterky, 1986). This paper contributes to this literature by linking changes in utilization with evidence of over-prescription of antibiotics.

The analysis exploits a unique dataset obtained from the government regulator COFEPRIS (Federal Commission for the Protection against Sanitary Risks) that registers PADOs' address and date of entry. This roster includes 2,354 PADOs from 2000 to 2014. I combine these data with public administrative data on clinic-level outpatient utilization rates by diagnosis, two rounds of the National Health Survey (ENSANUT), and city-level penicillin sales records at all private pharmacies.

In the first part of the paper, I begin by analyzing substitution patterns in response to PADO entry, focusing on public outpatient clinics. I then fill in the gaps on substitution from existing private providers and total changes in outpatient care.

Concentrating on the juxtaposition of public and private primary care (Das et al., 2016), and taking advantage of the availability of granular data for the public sector, I analyze the effect of the first PADO entry in a public clinic's catchment area on overall utilization following an event study design. This captures the effect of expanding the choice set of healthcare providers separately from competition effects among retail clinics in an area.

I find that the first PADO entry within a catchment area is associated with a gradual but permanent substitution away from public clinics of 5-6%. This finding is similar to substitution away from emergency room use in the US (Alexander et al., 2017; Sussman et al., 2013).[4] I also show that this effect is driven by acute respiratory infections.

Two important challenges arise. First, I document that first PADO entry is motivated by a spike in public utilization. This could confound the estimates due to mean reversion bias. I verify that this is not the case through an augmented specification including regional trends that account for unobserved fluctuations in local epidemics and demand for healthcare, as well as through a synthetic control exercise based on clinics that do not experience any entry throughout this period.

Second, potentially missing PADOs in the COFEPRIS dataset may bias the results. In online appendix B, I validate the roster for a small subsample by comparing observed PADOs with the true number obtained through manual counts in Google Maps. I discuss the potential bias in Section 4.1, and provide results on simulated data in online appendix C, which suggest attenuation bias. I calculate an upper bound on the magnitude of the reduction in public outpatient use following first PADO entry of 9%.

To fill in the gaps on substitution away from other private providers and overall changes in outpatient use, I exploit survey data from the 2006 and 2012 ENSANUT in a difference-in-differences (DD) framework. I cannot reject that substitution occurs from both public and private providers in the same proportion, and can reject positive effects on the overall probability of seeking outpatient care conditional on being sick. Hence, I find no evidence of new doctor visits, consistent with findings for retail clinics at pharmacies in the US (Pollack and Armstrong, 2009; Laws and Scott, 2008).

[4]There are many contextual differences in the retail clinic market between Mexico and the US. Alexander et al. (2017) emphasize the role of transparent prices at retail clinics. This is not a salient issue in Mexico, especially since care in the public system is free. Furthermore, ERs are less widely used as a substitute for doctor vists in Mexico. In the US, there were 45.1 ER visits per 100 persons in 2014 (National Hospital Ambulatory Medical Care Survey, CDC), while in Mexico there were only 8.6 (SSA data).

In the second part of the paper, I turn to characterizing quality. I focus on prescribing behavior for antibiotics, which speaks directly to misaligned financial incentives at the retail clinics. I then estimate effects on hospitalizations as a proxy for health.

Given that the estimated substitution effects are concentrated around respiratory infections, and due to the obvious links between the retail clinic and the pharmacy, I explore whether PADOs have larger financial incentives to prescribe medically unnecessary drugs, particularly antibiotics, relative to other providers. I analyze prescription practices in relation to PADO expansion using penicillin sales records at the city level through a DD.

The challenge is to isolate the effect of PADO expansion from any other city-level, contemporaneous changes in demand for healthcare and epidemiological prevalence. Regional trends account for local epidemiology, and controls for private pharmacies (regardless of retail clinics) proxy for shifts in demand for healthcare.

I find that an additional PADO per capita is associated with a 14% increase in per capita sales of stronger penicillin, which is mostly driven by generic complex penicillin. To the extent that these shifts toward stronger penicillin are medically unnecessary, PADOs provide lower quality of care in response to financial incentives. This may negatively impact health and may foster bacterial resistance in the long run.

These findings speak directly to the literature characterizing prescription practices in multiple contexts, including induced demand (Currie et al., 2011; McGuire, 2000; Iizuka, 2007), effects of increased competition (Bennett et al., 2015; Bennett and Yin, 2016) and prescription differences by type of provider (Das et al., 2016).

Attempting to identify health effects, I focus on public hospital admissions due to data availability. Admittedly, this is a severe health outcome, but complications from misdiagnosis at the primary care level may result in inpatient care, particularly in the case of infections (Weinberger et al., 2011). Using the same event study strategy as before and administrative data for inpatient care, I show that the first PADO entry has no significant impact on inpatient utilization rates, suggesting that along this extreme dimension, PADO care is not

significantly worse. This does not rule out other health effects nor increases in bacterial resistance.

As a coda, the final part of the paper complements these findings by showing how PADO presence correlates with characteristics of public and private healthcare providers in the 2012 cross-section of the ENSANUT. The results suggest that existing low-cost private providers compete with PADOs by lowering prices and time spent with patients. There is no effect for high-cost private providers along the same dimensions, nor for public providers in terms of waiting times or time spent with patients.

Overall, these results have important implications. First, there is no evidence that PADOs induce new doctor visits, suggesting instead that their use is all due to substitution. Second, PADOs face a financial incentive that leads them to overprescribe stronger penicillin relative to other providers. Finally, PADOs may affect the quality of care of existing private providers by competing for the same pool of patients. From a policy perspective, these results inform the need for stronger regulation of private providers, particularly innovations that are tightly linked to market incentives to over-treat. Although these providers have a potential upside, these downsides must be addressed.

The rest of the paper is organized as follows. Section 2 provides context on PADOs. Section 3 describes the data. Section 4 explores the effect on outpatient use. Section 5 characterizes the relative quality of care of PADOs. Section 6 considers market responses to PADOs. Section 7 concludes.

2 Pharmacy-Adjacent Doctors' Offices in Mexico

The healthcare system in Mexico is comprised of a public and private sector. The public system officially insures 73% of the population through their own network of public providers (2012 National Health Survey, ENSANUT). This public system is made up of disjoint institutions targeting different populations. The two main subsystems are the Mexican Social

Security Institute (IMSS) for formal workers, and the Social Protection System in Health (*Seguro Popular* or SP) for informal workers and the unemployed.[5] Private insurance, to be used with private healthcare providers, is primarily employment-based at higher wage levels. Less than 1% of the population is privately insured. For more details on how the healthcare system is organized in Mexico, see section A in the online appendix.

Public healthcare in Mexico is not universal in practice, is unequal in geographic access, lacks infrastructure, and has important supply shortages and long waiting times (OECD, 2016). Private health services on the other hand are very costly and paid mostly out-of-pocket (OOP). Private healthcare is a segmented market, with providers differentiating themselves by price and perceived quality. Despite low private insurance rates, 25% of the population indicate private doctors and clinics as their main primary healthcare provider, while 38% report getting medical care at a private provider for their last bout of sickness, conditional on seeking care (see Tables A1 and A2 in the online appendix).

Healthcare in Mexico is very inefficient. This is reflected both in the mismatch between system enrollment and utilization, as well as in high OOP health expenditures. Around 30% of public system affiliates actually seek private primary care (ENSANUT 2012), and according to the WHO's NHA indicators for 2014, the share of OOP out of total health expenditures in Mexico was 44%, well above the 33% average for Latin American countries. Within this context, private-market alternatives such as pharmacy-adjacent doctors' offices (PADOs) have appeared.

Similar to retail clinics, PADOs consist of a doctor's office located within a private pharmacy, offering outpatient consultations on a first-come, first-served basis. PADOs are set up and owned by pharmacies themselves. There is a limited array of services provided, with a focus mostly on acute infections. Services vary considerably across pharmacies, although most do not provide gynecological services nor open-wound care (Díaz-Portillo et al., 2015).

[5]The Ministry of Health (SSA) is directly in charge of SP, and I refer to SSA providers with the understanding that insurance is provided by SP. The public system insures 30% of the population at IMSS, and 38% at SSA. Smaller subsystems cover the remaining 5%.

PADOs operate during usual pharmacy business hours (including Saturdays and Sundays at a majority of locations), and waiting times are 21 minutes on average, or roughly a quarter of the waiting times in the public sector (ENSANUT 2012).[6] Consultations cost on average 39 pesos (3 USD), and many are even free, while traditional private providers charge 269 pesos on average (see Table A3 in the online appendix).[7]

The first PADOs appeared in 1997 at a chain pharmacy, *Farmacias Similares*, with a very gradual expansion over the next years. In August 2010, the government passed a law prohibiting over-the-counter (OTC) sales of antibiotics, one of the most lucrative drugs for pharmacies (Wirtz et al., 2008). Consequently, there was a huge expansion in new PADO entrants, mostly from chain pharmacies.[8]

To open a PADO, a pharmacy must obtain a notice of operations from the Federal Commission for the Protection against Sanitary Risks (COFEPRIS). While similar to a permit, no government approval is necessary. As such, many pharmacies hastily adapted part of their storage or shelf space, with minimal infrastructure investments (FUNSALUD, 2014). Additional regulations established in September 2013 are relatively lax.[9]

3 Data

3.1 PADO Roster

This paper uses a unique dataset obtained from the government regulator COFEPRIS, listing the notices of operations filed by each PADO. The data includes the PADO address - which

[6] It should be noted that many public outpatient clinics are only open from 8 am to 3 pm, Monday through Friday, while PADOs offer a much more accessible schedule (OECD, 2016).

[7] In 2012, 12 Mexican pesos = 1 USD.

[8] Santa-Ana-Tellez et al. (2013), Dreser et al. (2012), and Rubli (2017) examine the consequences of this law, including the impact on antibiotic sales, responses by pharmacy associations and interest groups, and health and distributional effects.

[9] Pharmacies may not have direct physical communication with the doctor's office, PADOs should comply with minimum infrastructure and equipment requirements, and doctors must display a copy of their medical degree.

allows me to determine its geographic coordinates - and the date when the document was filed. This dataset registers 2,354 PADOs from 2000 to 2014.

Figure 1 plots the cumulative number of PADOs in the COFEPRIS roster over time from 2007 to 2014, as well as the number of entrants by week. Note the change in the trend of total PADOs in mid-2010. As noted earlier, the timing of this expansion in PADO entry coincides with the announcement and implementation of a regulation limiting OTC access to antibiotics throughout Mexico.

Three points should be noted. First, I only observe the filing date, which may differ from the date when the PADO actually opened. Given the setting, where filing is a relatively simple bureaucratic process, it is unlikely that this potential mismatch in the filing and opening dates would be large.

Second, the data do not record PADO exit, since regulations do not require them to notify COFEPRIS when exiting the market. Anecdotal evidence suggests little to no exit during this period. Pharmacies able to pay the fixed cost of setting up a doctor's office are unlikely to have gone out of business.

Lastly, it is possible that there are missing PADOs in the roster. A report commissioned by COFEPRIS and prepared by a private consulting company lists 15,000 PADOs in existence in 2014 (see for example, FUNSALUD 2014). The reasons behind this discrepancy are unclear. Notices may have been misfiled or were not reported to the central COFEPRIS office, or it may simply be a miscalculation on behalf of the consulting company.

To verify these claims, I perform simple back-of-the-envelope calculations that suggest that the true number of PADOs in 2014 was actually between 6,000 and 10,000. I base these calculations on the distribution of PADOs across pharmacy chains detailed throughout the report, and use reliable industry data on the number of pharmacy locations by chain to back out the implied number of PADOs (see online appendix B for more details).

I undertake two exercises to validate the COFEPRIS dataset (results available in online appendix B). First, using survey data from ENSANUT, I show that the PADOs in my roster

are a good predictor of reporting PADO care conditional on being sick. Second, using Google Maps, I obtain PADO counts manually for a random subsample of geographic areas. I show that (i) there is a strong correlation between the true and observed PADOs within an area, (ii) the number of missing PADOs is not correlated with the total number of true PADOs in an area, and (iii) PADOs at independent or non-chain pharmacies are more likely to be missing in the roster. Sections 4 and 5 provide a discussion of the potential bias that may stem from these missing data, given the identification strategies employed.

3.2 Utilization Data

The data for utilization at public outpatient clinics come from the Ministry of Health's (SSA) Reported Cases Dataset from 2007 to 2014. This information is collected on a weekly basis, and contains all new diagnoses at the clinic level for all public health centers. I obtain geographic coordinates from SSA's Infrastructure Dataset for 2014. Within these data, I am able to identify acute respiratory infections (ARIs) and other conditions, based on ICD-10 codes (see section E in the online appendix for a list of conditions classified as ARIs).

Each public outpatient clinic is legally required to report this information. Although some private clinics also report this data, their compliance rates are extremely low. Utilization rates are reported in the data, using a local estimate of the population based on the census. I use this variable in order to account for differences in local market sizes.

Note that the Reported Cases Dataset only includes information on new diagnoses. Any visit due to an already diagnosed chronic condition will not appear in these data, as long as that diagnosis was made at a public health center. Hence, this dataset provides a more accurate picture of acute conditions such as infections, and one must be cautious when making conclusions regarding utilization rates due to chronic diseases.

I also exploit survey data from the 2006 and 2012 ENSANUT, focusing on questions about outpatient utilization conditional on having been sick. This is a nationally representative survey conducted every six years by the National Public Health Institute (INSP).

Lastly, I also analyze inpatient records from the Reported Cases Dataset, as well as admissions data for a subset of hospitals from 2007 to 2014. The advantage of the former is that it contains information from all public hospitals, while the latter only includes hospitals managed by SSA. However, in the Reported Cases Dataset it is impossible to distinguish hospitalizations from emergency room care.

3.3 Penicillin Sales Data

I obtain detailed, disaggregated sales data at private pharmacies for all class J01 penicillins on a monthly basis from 2010 to 2012. This information is compiled by the leading pharmaceutical data firm in Mexico, Knobloch Group (KG).[10] The data records the name of the product, dosage-units sold, and total revenue at the city level.[11,12] Note that this unit of analysis differs from the precise geographic coordinates of public health centers. Matching publicly available records compiled by COFEPRIS, I assign the chemical composition and manufacturer to each penicillin, as well as whether the product is generic or brand-name.

4 Effect on Utilization of Outpatient Services

This section presents the estimates of the effect of PADOs on outpatient service utilization. The first subsection calculates the effect for public outpatient clinics using an event study design. The second subsection uses survey data and an alternative specification to fully characterize changes on utilization for all outpatient services.

[10]The majority of pharmaceutical firms in Mexico use KG data in their marketing strategies, and anecdotal evidence from pharmaceutical company leaders indicates that their information is very reliable. I was able to purchase a small subsample of the data, which is why I limit this analysis to three years and to penicillins only. Further work must be done in order to characterize results for other antibiotics, other drugs, and other time periods.

[11]KG normalizes sales volume to dosage-units. Based on common physician prescription practices, this number represents units sold for a full course of treatment.

[12]KG actually analyzes "local urban markets". These correspond to 609 cities in Mexico, as well as 23 zones comprising Mexico City.

4.1 Public Outpatient Clinics

4.1.1 Empirical Strategy for the Event Study

To estimate the impact of PADO entry on utilization at public clinics, I exploit the fine geographic and temporal data within an event study design. The first step is to determine public outpatient clinic catchment areas. This is the smallest definition of a local health market. Beneficiaries of the public system in Mexico are assigned to the closest clinic, and the literature has shown that distance is a key variable in health center choice (Scott, 2000).

According to SSA's official infrastructure and planning documents, clinic catchment areas are determined as a 5 kilometer radius around the clinic, although in certain urban areas they can be smaller (2.5 km) and larger in rural areas (10 km).[13] Therefore, I define catchment areas as a 5 km radius around each health center, although results are robust to smaller areas. Note that there may be overlap in catchment areas for some clinics, especially in large urban centers and between clinics from different subsystems.

I then overlay the PADO roster to obtain entries from 2007 to 2014 within these catchment areas.[14] For each public outpatient clinic, I restrict PADO entries to those occurring between 2008 and 2013. This allows me to observe trends in the outcome variable before and after entry for at least a full year, even for very early or very late events. I further restrict the analysis to the first entry only, in order to disentangle the actual effect of expanding the patients' choice set from competition effects between PADOs in the same local market.

Not all public clinics have a PADO nearby, and not all PADOs in the roster are within 5 kilometers of a public clinic. From a total of 16,865 public outpatient clinics, only 15.5% or 2,260 ever register a PADO entry within their 5 kilometer catchment area during this period. Furthermore, the first entry in these 2,260 catchment areas is given by 459 unique PADOs, since PADOs may locate in the intersection of catchment areas. Regardless of this overlap, I

[13] SSA-MASPA (*Modelo de Atención a la Salud para Población Abierta*), 1995; SSA-MIDAS (*Modelo Integrador de Atención a la Salud*), 2006.

[14] Note that more than one PADO may enter in a given week and catchment area. Out of all observed entries, 82% are single entrants, 11% are two PADO entrants, 3% are three entrants, 2% are four entrants, and the remaining 2% of entries are those with five or more entrants.

am effectively observing the first PADO entry that provides a new option for outpatient care within a local market for healthcare (see online appendix D for more details).[15] Figure 2 shows a map with the location of these public outpatient clinics.

Table 1 presents summary statistics. Panel A refers to public outpatient clinics, distinguishing between the 2,260 clinics in my sample versus the remaining ones.[16] Descriptives are provided for outcome variables, subsystem institution, some infrastructure characteristics, and details on PADO entry. The differences between the analyzed sample and the rest of the clinics tend to be statistically significant, mostly due to the fact that PADOs are an urban phenomenon. In general, sample clinics have fewer diagnoses, and have a larger capacity and are better staffed than the rest. Over this period, 1.6 PADOs enter each catchment area per year on average.

Panel B in Table 1 shows information on PADO entries, grouping them into first entries and subsequent entries. Once again, the differences between these groups are all significant. Note that first entries are more likely to be single entrants and are more spaced out over time than subsequent entries.

The empirical design to analyze the effect of first PADO entry on public outpatient utilization rates follows an event study methodology. For the total of 2,260 clinic catchment areas for which I observe PADO entry between the first week of 2008 and the last week of 2013, I construct a balanced panel recording the event date for the first entry. I then estimate the following equation:

$$y_{ct} = \beta_{-A}\mathbb{1}_{[t-E_c\leq -A]} + \sum_{d=-A+1}^{B-1} \beta_d \mathbb{1}_{[t-E_c=d]} \quad + \beta_B \mathbb{1}_{[t-E_c\geq B]} + \gamma_t + \theta_c + \varepsilon_{ct} \tag{1}$$

[15] To verify that the fact that a given PADO provides a first entry event for multiple catchment areas is not confounding the results, I also construct catchment areas as Thiessen polygons. The main findings hold, albeit more noisily, and are available upon request.

[16] Section F in the online appendix provides more details on the differences between the sample clinics and those with a first entrant in either 2007 or 2014.

where y_{ct} is the utilization rate of outpatient services at public clinic c in time period t, $\mathbb{1}_{[\cdot]}$ is the indicator function, E_c is the period in which clinic c's catchment area receives its first PADO, $A, B > 0$ are natural numbers that define an arbitrary size for the vector of leads and lags, γ_t is a time period fixed effect, θ_c is a clinic fixed effect, and ε_{ct} is the idiosyncratic error term.

The outcome variable refers to the number of new diagnoses in a particular clinic divided by the population estimate provided in the data. I refer to this as the utilization rate. The implicit assumption behind this interpretation is that the first entry is not significantly changing epidemiological trends, such that this variable does not reflect changes in the prevalence of diseases.

Time period fixed effects remove any seasonality in utilization rates common to all catchment areas in the sample, while clinic fixed effects imply that the effects are estimated only from variation within clinics over time. The main source of bias in equation 1 comes from time variant unobservables at the clinic level, such as unobserved trends in demand for health. I therefore also include regional trends in an augmented specification, using a latitude-longitude grid cell by month fixed effect (see Figure 2).[17]

4.1.2 Effect of First PADO Entry on Public Outpatient Utilization

The main results for outpatient utilization rates from estimating equation 1 are shown in Figure 3. Although weekly-level observations are maintained, the leads and lags are grouped by four-week periods for clarity. The specification considers six four-week periods post-entry, and a full year (13 four-week intervals) pre-entry. Standard errors are clustered at the clinic level to allow for any serial correlation in the error term within clinic catchment areas.

Figure 3a plots the coefficients for the indicators in equation 1, with 21 to 24 weeks before entry as the excluded category (this allows for a clearer visualization of pre-trends, keeping

[17]To be clear, I construct latitude-longitude degree grid cells by interacting latitude and longitude degrees (ignoring minutes and seconds). Another alternative is to include state by month fixed effects. Results are maintained with this specification and are available upon request.

in mind that the relative distance between point estimates does not vary with the choice of excluded category). Each coefficient series is shifted by a constant so that the mean of the regression coefficients is equal to the sample mean of the dependent variable.

Utilization rates at public clinics remain fairly constant up to 8 weeks before entry. However, there is an increase in utilization rates 4 weeks before entry. Although the point estimate is not significant (implying that utilization rates are not statistically different from rates during the excluded period), an alternative specification pooling all time periods prior to the first four weeks before PADO entry shows that β_{-4} is statistically different from the pooled estimate at the 99% confidence level. Note that a test of the original estimates of whether β_{-4} equals β_{-8} also rejects the null at the 99%. This suggests that entry appears to be demand-driven.

Post-entry, the estimates exhibit a downward trend, becoming stable at the 12 week mark. These coefficients are statistically significant and similar in magnitude, implying a reduction in utilization rates at public clinics of 5-6% relative to levels during the excluded period. The gradual decline may reflect the speed at which information on PADO entry spreads across the catchment area. Alternatively, PADOs may be an experience good, so that substitution is not immediate.

The estimated pre-trends are an important concern for identification. If first PADO entry occurs in catchment areas where utilization is rising, then the subsequent decline may simply correspond to reversion to the mean. I undertake two checks to provide convincing evidence that this is not the case.

First, I include regional trends in the estimating equation. If the results are due to mean reversion, then this should attenuate both the pre-trend and post-entry effect. The results from estimating equation 1 with latitude-longitude grid cell by month fixed effects are shown in Figure 3b. The estimated coefficients follow a similar pattern, with the regional seasonal effects smoothing out the pre-entry trends. A test of whether β_{-4} equals the preceding five estimates in a regression that pools these indicators rejects the null only at the 90% level.

Although there still seems to be a slight increase in utilization pre-entry, the magnitude is much smaller and less significant. Importantly, the regional trends have no impact on the estimates post-entry relative to Figure 3a.

Second, I construct a set of synthetic controls from the public outpatient clinics for which I never observe entry that serve as a counterfactual to the true entries. Due to computational power issues, I collapse the clinic-weekly date data into clinic-monthly date observations, and set $A = 13$ and $B = 6$ as before.

For each of the 2,260 treated clinics, I randomly choose a 20% subsample of the 5,010 untreated clinics belonging to SSA with at most 52 weeks with zero cases over this 8-year period.[18] I then estimate a vector of weights for the subsample of untreated clinics, such that the utilization rates of the synthetic control closely match those of the treated clinic in the 12 months preceding entry, as well as the overall average pre-entry.[19] These weights are then used to construct the post-entry rates for the synthetic control of each clinic, resulting in a dataset of 2,260 synthetic controls, each corresponding to a treated unit.

Figure 4 plots the coefficients for the synthetic control data and the actual entries. Figure 4a shows the main specification, while Figure 4b includes the regional trends given by latitude-longitude grid cell by month fixed effects. If the main findings are due to mean reversion bias, then the synthetic control estimates should also display a similar downward trend post-entry. However, the results show that while the pre-trends are matched, the post-entry estimates are significantly different. The synthetic control shows no effect of PADO entry on utilization rates.

The results including regional trends in Figure 3b and the results of the synthetic control exercise in Figure 4 provide reassurance that the main findings are not driven by reversion to the mean.

[18]This restriction is imposed since the zeros are non-informative for the construction of the control and because the majority of treated clinics are SSA clinics (68%).

[19]This method relies on minimizing the mean square prediction error, in terms of the deviations of the synthetic control's utilization rates in the 12 months before entry from the actual observed rates for the treated clinic (Abadie et al., 2010).

Potentially Missing Data

As noted above in Section 3, missing data in the COFEPRIS roster may be a source of potential bias. Intuitively, in the event study design, bias may stem from two sources: unobserved additional entries in the weeks following an observed first entrant, and misclassifying a higher order entrant as a first entry. The former is less likely to occur in smaller geographic areas (such as catchment areas), while the latter depends on the assumptions on how the marginal effect of entry depends on true entry order.

While it does seem that the COFEPRIS data are incomplete, each entry observed is a true entry, and the total entries are a noisy measure of the true total PADOs (see online appendix B). Moreover, the probability of missing a PADO is constant on either side of entry. As such, this measurement error will lead to attenuation bias. Online appendix C presents results on simulated data to support this claim. Each simulation makes different assumptions on the true count and the relationship between the true and observed counts.

The simulations show that the attenuation bias is larger as (i) the true number of PADOs grows; (ii) the marginal effect of entry decreases with entry order; (iii) the probability of observing an entry decreases with total entries in the catchment area; and (iv) as entries with smaller marginal effects on utilization are more likely to be observed.

The evidence suggests that the attenuation bias is relatively small. First, simple calculations in online appendix B show that the true number of PADOs is smaller than 15,000. Since PADOs continue entering local markets during this period, it is reasonable to assume that marginal effects do not decrease much with entry order. Lastly, the process for obtaining a notice of operations and the structure of COFEPRIS (for example, regional offices located in urban centers) suggests that entries are more often observed in areas with more entries, and for entries with larger marginal effects (for example, in urban areas; see online appendix D).

Therefore, the simulations in online appendix C suggest an attenuation factor for the estimated effect of roughly 0.8 of the true effect. This implies that the true impact is

a reduction of around 9% in public outpatient care utilization due to first PADO entry. Importantly, the overall conclusion, that PADO entry leads to substitution away from public clinics, holds.

Results by Diagnosis

The fact that many PADOs opened as a response to the law limiting OTC sales of antibiotics suggests that common symptoms for which there is high patient-induced demand for antibiotics could drive the effects. Descriptively, ARIs are the single most important reason for visiting a PADO, according to Pérez-Cuevas et al. (2014) and the 2012 ENSANUT. Therefore, Figure 5 shows the estimates of equation 1 separately for ARIs and the rest of the diagnoses (non-ARIs).[20]

In Figure 5a, the substitution effects for ARI services closely match the pattern found for all cases in Figure 3, while there is little evidence of substitution for non-ARI services, as shown in Figure 5b. This indicates that ARIs drive the substitution results, as expected. Overall, this suggests that individuals adjust their choice of provider differentially by symptoms related to OTC restrictions on antibiotics, and motivates the exploration of PADO quality through antibiotic prescription practices in Section 5.

Robustness Checks

I perform a series of robustness checks on the main results shown in Figure 6. Figure 6a restricts to events where the second registered entry occurs at least 25 weeks after the first entry, reducing the events from 2,260 to 1,463. If the main effect is confounded with effects from future entrants within the catchment area, then this restriction would attenuate the results. However, Figure 6a shows the same patterns in the estimates. Note that this restriction might not be sufficient for isolating the effect if there are missing PADO entries. Nevertheless, this finding is reassuring.

[20]Non-ARIs can also be broken down into categories, such as gastrointestinal and chronic diseases. However, results are very similar to grouping them together. Individual results are available upon request.

Figure 6b restricts the events to clinics that only register strictly positive rates per week within a 24-week window around first PADO entry. This decreases the number of events to 1,296. The results still hold under this restriction, indicating that the zeros do not drive the estimated effect.

Lastly, I consider a placebo test that randomly shuffles entry dates across catchment areas. For each clinic c, the entry date of clinic c' is randomly assigned, with $c \neq c'$. This maintains the distribution of entry dates across clinics. I repeat this placebo exercise 100 times. Figure 6c presents the results averaged over these 100 iterations, finding no discernible pattern in the coefficients, which are statistically indistinguishable from zero.

Interpretation of Findings

The main results above suggest that entry is demand-driven, given the increase in utilization around 4 weeks prior to entry. The relatively lax regulation and low infrastructure requirements suggest that it is indeed plausible for PADOs to set up and start operating in that time frame (see for example, FUNSALUD 2014). Once the first PADO enters the clinic catchment area, utilization rates at these clinics decline and reach a lower level than the one in weeks prior to entry. Additional specifications rule out mean reversion bias.

With a weekly utilization average pre-entry of 54.9 per 100,000, the estimates imply a reduction of around 5-6%. A simple back of the envelope calculation would imply that at least 40% of PADO visits are just substitution away from public providers.[21]

These results only imply net substitution away from public outpatient clinics. These estimates cannot distinguish the number of new doctor visits that would not have occurred in the absence of the PADO (individuals switching from no medical care to PADOs). Also note that chronic disease management is unobserved in this dataset, since only new diagnoses are registered. Therefore, I cannot distinguish whether this decline in utilization is possibly

[21]Each PADO operates about 12 hours a day, and can therefore see about 24 patients a day at full capacity. Public clinics offer around 165 daily consultations. Therefore, the effect implies 10 visits less with PADO entry, or 40% of PADO patients.

offset by increases in chronic disease management visits. Likewise, changes in public care characteristics, such as congestion and time spent with the patient, are unobserved here. Sections 4.2 and 6 attempt to tackle these questions using survey data.

4.2 All Types of Outpatient Care

The previous subsection showed that first PADO entry within a public outpatient clinic's catchment area decreases utilization rates at that clinic by 5-6%. I now show how PADOs affect private and total outpatient utilization, exploiting survey data from the 2006 and 2012 ENSANUT in a difference-in-differences (DD) framework.

4.2.1 Empirical Strategy

Due to data limitations, I cannot follow the same event study design as before. The estimating equation here is given by:

$$care^{b}_{imy} = \beta PPC_m + X_{imy}\phi + \theta_m + \gamma_y + \varepsilon_{imy} \tag{2}$$

where $care^{b}_{imy}$ is an indicator for the type of care b chosen by survey respondent i in municipality m in survey year y, where b can be PADO care, non-PADO care, private care, public care or any outpatient care, conditional on being sick; PPC_m is the total number of PADO counts per capita according to the COFEPRIS dataset; X_{imy} is a vector containing individual and municipality level controls; θ_m are municipality fixed effects; γ_y are survey year indicators; and ε_{imy} is the error term. Standard errors are clustered by municipality.

The coefficient β indicates by how much an additional PADO per capita in a given municipality increases or decreases the probability of seeking type of care b conditional on being sick. For a causal interpretation, unobserved determinants of seeking care, such as preferences, provider characteristics, and demand for healthcare, must not be correlated with the number of PADOs per capita. Survey year fixed effects account for overall differences

between 2006 and 2012, while municipality fixed effects capture any time-invariant differences in unobservables across space.

The main threat to identification in equation 2 are unobserved factors that vary across space and time. One such concern is that municipalities with more PADOs per capita in a given year are those that also have a stronger demand or preference for healthcare. To account for this, I control for pharmacies per capita in municipality m, year y and its square – obtained from the Mexican Business Information System (SIEM) at the Ministry of the Economy. To the extent that increases in pharmacies (regardless of PADOs) is correlated with demand for healthcare, this variable should account for those differences.

Another important concern relates to measurement error, as PADO counts are aggregated at the municipality level for 2006 and 2012, assigning zeros to municipalities without any counts in the dataset. This may introduce some noise due to the potential missing data problem discussed above (see Section 3). However, as long as underreporting is uncorrelated with the true number of PADOs - as shown above - and uncorrelated with other unobserved factors that determine utilization, this will lead to attenuation bias. Any estimated effects are therefore a lower bound on the true effect.[22]

Similar to the exercise above, I also decompose the effect by type of illness. Following the same strategy in equation 2, the dependent variable is now defined as:

$$care_{imy}^{bs} = \begin{cases} 1 & \text{if } i \text{ got care at } b\text{, conditional on being sick with illness } s \\ 0 & \text{otherwise, conditional on being sick with illness } s \end{cases}$$

[22]The common, simplest setup for classical measurement error assumes that we observe $\tilde{x}$ instead of the true x in a regression of the form $y = \beta x + \epsilon$, and that the measurement error u has mean zero, and is uncorrelated with x and with ϵ (Cameron and Trivedi, 2005). In this particular context, it is safe to assume that PADO underreporting is uncorrelated with the true number of PADOs (see Section 3). However, since all the counts are true PADOs, $E(u) = 0$ does not hold. Note that this assumption is not critical for the attenuation bias result, as can be easily shown by defining a mean zero measurement error term $r = u + k$, where $E(u) = -k$.

Note however that s may be endogenous in the survey. For two individuals with the same ailment, s may differ depending on type of care b and on whether the individual even got any type of care. As such, caution must be practiced when interpreting these results.

4.2.2 Effect of PADOs on Utilization Using Survey Data

Table 2 shows the estimates of equation 2. The following controls are included: pharmacies per capita by municipality-year and its square, respondents' age, gender, and dwelling indicators for having a dirt floor, electricity, piped water, and sewage. Standard errors are clustered at the municipality level.

Panel A considers all illnesses. Column 1 shows the estimate for PADO care, while column 2 considers non-PADO care (public or private care). Note that in the 2006 ENSANUT, PADO care was not listed as an option for type of care sought, since PADOs were not very prevalent. The former shows a positive and significant coefficient, and the latter is negative and significant. This indicates that an additional PADO per 100,000 people in a municipality increases the probability of PADO care conditional on being sick by around 3 percentage points (pp), and decreases the probability of other types of care by 9 pp.

Columns 3 and 4 attempt to decompose this effect into substitution away from private and public providers. The coefficients are similar in magnitude, but insignificant. The large standard errors prevent ruling out that substitution occurs in more or less equal proportions away from private and public providers.

Lastly, column 5 considers any type of outpatient care. The coefficient is negative and significant at the 90% level. However, given the lack of precision, I interpret this to be a statistical zero. Importantly, I can reject at the 99% that this coefficient is strictly positive. This finding is important, since it suggests that PADO entry does not induce new doctor visits. This is consistent with the literature for the US, analyzing the expansion of retail clinics at pharmacies (Pollack and Armstrong, 2009; Laws and Scott, 2008).

Panels B, C and D consider different types of disease, specifically for ARIs, gastrointestinal diseases (GIDs), and chronic diseases, respectively. The estimates for ARIs are very similar to the ones for all illnesses in Panel A. The coefficients for GIDs and chronic diseases are all very close to zero and statistically insignificant. Note that conditional on being sick, 50% of respondents identify their illness as an ARI. The prevalence for GIDs and chronic diseases is 6 and 7%, respectively. This result once again suggests that PADO care and its effect on other types of care is concentrated around ARIs. Interestingly though, there do not seem to be increases in outpatient care for other conditions.

In summary, this exploration indicates that substitution occurs in roughly the same proportion from both public and private providers, and that there is no evidence of increased utilization of professional medical care associated with the expansion of PADOs.

5 Relative Quality of Care at PADOs

This section analyzes the relative quality of care at PADOs in order to shed some light on the implications of the observed substitution patterns, mostly motivated by the close link between PADO expansion and ARIs as documented above. First, I focus on doctor incentives, analyzing how PADO expansion correlates with types of penicillin sold. If PADO doctors have a larger financial incentive, then they could be shifting prescriptions towards more profitable types, regardless of epidemiological trends. Second, I analyze inpatient care as an extreme (but not uncommon) health outcome. If PADO quality is significantly worse relative to other outpatient options, then hospitalizations could increase (especially among vulnerable populations such as children and the elderly).

5.1 Sales of Penicillin

As outlined above, it may be that patient-induced demand for antibiotics drives the success of PADOs, which in turn may impact prescribing behavior. Therefore, I explore whether PADO

presence is associated with different penicillin prescription practices. If local epidemiology is unchanging, then these effects will be indicative of financial incentives to overprescribe.[23] PADOs may respond to these incentives on the extensive and intensive margin, although the data only allow me to estimate the latter.

Penicillin remains the most prevalent antibiotic prescribed for the treatment of bacterial infections, especially ARIs. There are two main types. The first is a simple, basic aminopenicillin (for example, amoxicillin), while the second is a more potent drug that combines aminopenicillin with a β-lactamase inhibitor (such as amoxicillin clavulanate).[24] Due to the risk of increasing bacterial resistance, organizations like the WHO warn against prescribing stronger antibiotics as a first course of action (Leung et al., 2011), as well as warning against misuse. Note that there is a positive correlation between price and penicillin strength.

5.1.1 Empirical Strategy

This section uses data on sales of penicillin from Knobloch Group, from January 2010 to December 2012. The data records dosage-units and total revenue at the city-month level. I merge this dataset with the PADO count data. I observe 632 cities or local urban markets, of which 253 (40%) have at least one PADO during this three-year period. In the main specifications, I include the local urban markets for which there are no PADO observations as true zeros. As a robustness check, I exclude them.

Matching records compiled by COFEPRIS allows me to distinguish pencillins by chemical composition and whether it is sold as a generic. For each local urban market and monthly date, I observe a total of 185 different varieties of penicillin, of which 131 (71%) are basic aminopenicillins and 75 are generics (41%). Within basic aminopenicillins, 61 (47%) are generics, and within combination penicillins, only 14 (26%) are generic. There are 51 different manufacturers, although for 79 of the 185 products I am unable to obtain a consistent match.

[23] This overprescription refers to the fact that these antibiotics are not medically necessary.

[24] Bacteria that are resistant to aminopenicillin produce enzymes called β-lactamase, which invalidate the potency of the drug.

Descriptive statistics for these data are presented in Table 3. Average units sold and average price per unit are shown for the entire data, as well as for those markets that have at least one PADO over this time period. Products are classified by chemical composition and by whether they are generic. Note that in general, basic aminopencillin is cheaper than more complex varieties of penicillin, and generics are less expensive than brands.

To analyze prescribing behavior, I estimate the following equation:

$$spc_{amt} = \beta PPC_{mt} + \gamma_t + \theta_m + \varepsilon_{mt} \tag{3}$$

where spc_{amt} are dosage-unit sales of product a in local urban market m in period t per capita, PPC_{mt} is the count of PADOs per capita, γ_t are month-year fixed effects, θ_m is a local market fixed effect, and ε_{mt} is the error term. An additional specification includes a local urban market by product fixed effect. Standard errors are clustered at the urban market level.

The estimate of the marginal effect of an additional PADO on sales per capita will be unbiased as long as the number of PADOs per capita is uncorrelated with unobservables that may influence per capita sales of penicillin. Month-year and market fixed effects capture common seasonality effects and market-specific differences in the outcome that are time-invariant, respectively.

The main confounder consists in time-varying unobserved factors. To capture local fluctuations in epidemiology and demand for health over time, augmented specifications include regional trends, (through a latitude-longitude grid cell by month fixed effect as before), and a quadratic trend by local urban market. Furthermore, measurement error in PADOs per capita will attenuate the results (see discussion above in Section 4.2).

I also analyze the (weighted) average price per unit sold for each period in each market using the same strategy. I define the dependent variable as $\bar{r}_{mt} = \frac{\sum_a R_{amt}}{\sum_a s_{amt}}$, with R_{amt} denoting the total revenue from sales of product a in market m in period t.

5.1.2 Effect of PADOs on Composition of Penicillin Sales

Table 4 shows the results on sales based on equation 3, decomposing the effect for each of the four categories determined by chemical composition and by whether or not it is a generic product. The regressions therefore include the interaction of PADOs per capita PPC_{mt} with an indicator for each of the four penicillin groups, as well as these indicators on their own. The main specification is shown in column 1. Column 2 substitutes the local market fixed effect with a market by product fixed effect. Columns 3 and 4 add regional flexible trends and quadratic trends by market to the main specification, respectively. Column 5 excludes markets without PADO counts in this period. All results are stable across specifications.

The estimates for the effect of PADOs on sales of basic penicillin, both generic and brand-name, are negative. Although not statistically significant on their own (except in column 2), a joint test of significance rejects the null hypothesis that they are simultaneously zero. In a specification that does not distinguish along the generic dimension, the estimate for the effect of an additional PADO per 100,000 on sales per capita of basic penicillin is a 7% significant decline.

The coefficients for the effect of PADOs on sales of complex penicillin in Table 4 are positive and highly significant for both generic and brand-name combination penicillin. The magnitude is larger for generics. Given the average sales per capita of these penicillin types, I estimate that an additional PADO per 100,000 leads to a 22% and an 11% increase in the per capita sales of complex generic and complex brand-name penicillin, respectively. Taking into account their product shares, this amounts to an overall increase in the sales of complex penicillin of 14%.

The results in Table 4 indicate a large shift in the composition of penicillin sales in correlation with the number of PADOs in the local market. To the extent that the fixed effects capture any unobserved preferences or demand for health, these estimates allow for a causal interpretation. The data show that complex penicillins are more expensive, and it is reasonable to assume that their profit margin is larger. This suggests that PADOs

are overselling patients, since these stronger drugs are most likely medically unnecessary. The implicit assumption is that the controls fully capture any changes in epidemiological dynamics, eliminating medical reasons to shift prescriptions as PADOs enter the market.

Note that the positive effect on sales of complex types is larger for generics, which are cheaper on average. A potential explanation is that the margin of profit is not necessarily positively correlated with the sales price. This would be the case if more pharmacies are producing their own generics, which are then prescribed by the PADO doctor. Anecdotally, many pharmacy chains with PADOs carry their own generics and have expanded their supply over the years (FUNSALUD, 2014).[25]

Table 5 presents the estimates for equation 3, using the weighted average price as the dependent variable. The coefficients across specifications are stable in magnitude, negative and significant at the 95% level. Given the average price, this implies an economically negligible decline of around 1%. This is due to the disproportionately larger shift toward *generic* complex penicillins.

Overall, the analysis on prescribing behavior shows an important shift from basic to complex penicillin that cannot be accounted for by epidemiological trends. The negative externalities of increased bacterial resistance due to antibiotic misuse may then have a negative impact on welfare in the long run.[26] This highlights the importance of regulations that restrict the overprescription of antibiotics especially at PADOs. Unfortunately, the data does not identify other types of antibiotics, nor is it possible to match sales with the type of provider that prescribed the drugs.

[25]See for example http://www.economiahoy.mx/ciencia-eAm-mx/noticias/7843122/09/16/La-venta-de-medicamentos-genericos-aumenta-un-15.html, accessed November 2016.

[26]Anecdotal evidence in the media points to PADOs as contributing to bacterial resistance. See for example http://www.eluniversal.com.mx/articulo/ciencia-y-salud/2017/02/28/crece-resistencia-de-12-bacterias-antibioticos-oms, accessed March 2017.

5.2 Inpatient Care

Having established that PADOs are overselling patients, I turn toward potential health impacts. Data availability constrains me to focus on hospitalizations as an extreme health outcome, exploiting the fine granularity of the data as before.

5.2.1 Empirical Strategy

I use two distinct but related data sources here. First, I analyze the Reported Cases Dataset, focusing now on inpatient care health centers. There are 1,061 public inpatient centers, although only 36.4% (386) have PADO entry in their catchment areas. Each hospital is near a public outpatient clinic, tightly linking these estimates to the substitution results at the outpatient level in Section 4.1. New diagnoses at inpatient facilities do not necessarily imply hospitalization (for example, emergency room visits). The second dataset is the Admissions Data for SSA Hospitals. These public records are available only for hospitals managed directly by SSA. The data include a total of 317 SSA hospitals, of which 91% (288) have a PADO entry within their catchment area.[27]

Due to the nature of this data, I follow the same empirical strategy as in Section 4.1.

5.2.2 Effect of First PADO Entry on Inpatient Care

Figure 7 presents the results from estimating equation 1 for both sets of data. Figure 7a corresponds to inpatient centers, and Figure 7b to SSA hospitalizations. In both cases, there does not seem to be any effect from PADO entry.[28]

To relate these findings to the substitution effects in Section 4.1, I determine the set of values that can be ruled out by the confidence intervals of these estimates. Consider the coefficient on the indicator for more than 20 weeks after entry. I can reject at the 90% confi-

[27]Note that in the Reported Cases Dataset, there are 608 inpatient care centers belonging to SSA. Therefore, the 317 hospitals observed here are roughly half of the total. Since reporting the hospitalizations data is not compulsory by law, it is possible that only a subset of SSA hospitals comply with this request.

[28]The results are similar when including regional trends in the form of latitude-longitude grid cell by month fixed effects. These are available upon request. Likewise, results are similar when restricting to ARIs.

dence level an effect larger or equal to 1.7 and 2.6 for inpatient care and SSA hospitalizations, respectively. Given the estimates for substitution away from public outpatient clinics, this implies that I cannot rule out that at most 50% of the decline in outpatient utilization ends up receiving inpatient care, and that 80% ends up admitted to an SSA hospital.

Alternatively, I reestimate equation 1 with a single indictor for the post-entry weeks. The estimates are -5.08 (standard error 3.81) and -0.67 (standard error 1.70) for inpatient care and SSA hospitalizations, respectively. For each, it is possible to reject a magnitude greater than 1.20 and 2.13. Since the same strategy yields a coefficient of -2.82 for public outpatient clinics, then I cannot reject that up to 43% and up to 76% of the outpatient substitution leads to either inpatient care or SSA hospitalizations, respectively.

I interpret these findings as evidence that doctor quality and overprescription at the PADO is not significantly worse relative to other doctors, at least in terms of complications leading to inpatient care. The underlying assumption here is that doctor quality in the public healthcare system is not changing with PADO entry within the time frame analyzed.

6 Private and Public Market Responses

This section now turns to characterizing potential market responses from existing private and public providers to the introduction of PADOs. I use the 2012 ENSANUT to estimate the correlation between PADOs and certain characteristics of private and public outpatient services in the cross-section.

6.1 Empirical Strategy

The estimating equation for this exercise is given by:

$$y_{im} = \beta PPC_m + X_{im}\phi + \varepsilon_{im} \tag{4}$$

where y_{im} is a potential outcome of interest measured in logs, and everything else is defined as above. Standard errors are clustered by municipality. For the private market, the outcomes are the price of a doctor visit and how much time the doctor spends with each patient. For the public market, I focus on the duration of the visit and waiting times. Note that these outcomes are recorded by respondents of the 2012 ENSANUT, not the providers themselves.

An important unobserved confounder is overall demand or preferences for healthcare at the municipality level, as this may impact both the number of PADOs per capita and the outcomes. Hence, I include pharmacies per capita and its square as controls. I also include municipality level controls in some specifications. However, I abstain from assigning a causal explanation to these relationships.

6.2 Relationship Between PADOs and Provider Characteristics

Focusing first on the private market (excluding PADOs), the natural log of the price of a doctor visit follows a bimodal distribution, indicating market segmentation. Hence, I calculate the overall effects as well as separately for the low and high-cost private markets. I use the terms "cost" and "price" interchangeably throughout, with the understanding that this is the amount paid by patients for a doctor visit.

The first section of Table 6 shows the outcomes for the private market, with price per visit in Panel A and visit duration in Panel B. Recall that private insurance rates in Mexico are extremely low, so that these are OOP expenditures. The first two columns show the estimates for the full sample, with the second column including municipality controls. Columns 3-6 split the sample based on the median of the observed cost of the visit. Columns 7-10 split the sample based on a predicted median cost. To obtain the latter, I regress the observed price on a series of sociodemographic indicators in the survey, and then use the estimates to predict the price paid by each respondent.[29]

[29]The sociodemographic indicators include household size, age, gender, dwelling characteristics as defined above, indicators for education level, an indicator for being married, an indicator for being employed,

Panel A reports negative coefficients for the full sample with large standard errors. Subsequent columns show that for the low-cost private market, the effect is negative and significant, while the effect is positive but insignificant for the high-cost private market. Panel B indicates that the full sample estimates for the duration of the visit are positive and insignificant. Stratifying by median price yields negative coefficients for the low-cost market and positive ones for the high-cost market. Estimates are not significant for the segmentation based on the true median price, but are significant under the predicted median price.

The results suggest that more PADOs in a municipality are associated with lower prices and less time spent with each patient for the low-cost private market, and no effect on prices and more time spent with each patient for the high-cost private market.

The second section of Table 6 shows the outcomes for public providers in columns 11-14, with time spent with patients in columns 11-12 and waiting times in columns 13-14. The estimated coefficients are all statistically zero, suggesting that the public market's congestion, as measured by waiting times and duration of visit, was unaffected by PADOs.

6.2.1 Full Distribution of PADO Effect on Service Characteristics of Traditional Private Doctors

In order to get a clearer picture of how PADOs correlate with private doctor prices and time spent with patients in the low and high-cost markets, I estimate a hazard model and plot the fitted cumulative hazard to show the full distributional response. Although hazards are usually implemented for duration models, in essence they calculate distribution functions, which is the relevant question here, with the objective of characterizing the full distribution of these associations.

Intuitively, for the price response I define durations as price increments, and register an event as whenever the price paid is reached for an individual. I then estimate the hazard and

indicators for public health institution affiliations, indicators for receiving government aid, pensions and remittances, and municipality controls.

plot the predicted distributions, distinguishing between both markets (high and low-cost) and between markets without PADOs or with one PADO per 100,000 individuals.

The procedure is as follows. I first discretize the natural log of the price of private doctor visits by dividing into quantiles. I then generate a pseudo-dataset, where each individual is observed for each price increment until the price paid is reached. Lastly, I fit the hazard model through a logistic regression of the following form:

$$\Pr(\bar{p} = p) = \sum_{\rho=1}^{\rho^{max}} \eta_\rho \mathbb{1}_{[p=\rho]} + \chi \mathbb{1}_{[\text{low market}]} + \kappa PPC + \lambda(\mathbb{1}_{[\text{low market}]} \times PPC) + \varepsilon \qquad (5)$$

where $\bar{p}$ is the price paid by the individual, p represents the price increments in the pseudo-data, $\mathbb{1}_{[p=\rho]}$ are indicators for each of the price increments (with the maximum price increment equal to ρ^{max}), PPC are PADOs per 100,000 individuals as before, and $\mathbb{1}_{[\text{low market}]}$ is an indicator for belonging to the low-cost private market as defined by the predicted median described above.

Using the estimates from this equation, I construct the predicted probability of paying a price for each of four groups defined by low vs high-cost market, and by zero vs one PADO per 100,000. I repeat the same exercise for the time private doctors spend with patients.

Figure 8 presents the results. The fitted cumulative distribution functions for the price of private doctor visits are shown in Figure 8a. For the low-cost market, the fitted cumulative hazard for one PADO stochastically dominates the one for zero PADOs. This is evidence that the cost of private doctors in the low-cost market is lower with the presence of PADOs than without. For the high-cost market, stochastic dominance goes in the opposite direction and the difference is smaller. This may suggest some increase in prices for these private providers with the presence of PADOs, perhaps because it is easier to price discriminate or as a way to signal quality.

Figure 8b shows the estimated cumulative distribution functions for time spent with patients for the same four groups. The direction of the relationships is the same as in

Figure 8a, suggesting that private doctors in the low-cost market reduce the time spent with patients in the presence of a PADO relative to no PADOs.

This exercise confirms the findings in the first part of Table 6. PADOs are associated with a decrease in prices and time spent with patients for low-cost private providers. This suggests that low-cost private providers compete with PADOs for the same pool of patients by lowering prices and increasing volume through shorter visit durations.

7 Conclusion

Private-market innovations in healthcare delivery are expanding in the developing world, and may be an efficient solution to healthcare provision challenges in those settings. Understanding the tensions at play is crucial for welfare evaluation. This paper focuses on evidence from retail clinics in Mexico to estimate the effect of new, innovative providers on healthcare utilization and quality, mostly through prescribing behavior.

The findings show that the first PADO entry decreases utilization of public outpatient services by 6%. There is no evidence of new doctor visits associated with PADO presence. I find that PADOs are associated with a large shift toward stronger antibiotics, without any significant implications in terms of inpatient care. Lastly, I show suggestive evidence that existing low-cost private providers compete with PADOs by decreasing prices and time spent with patients.

These results suggest limited gains in terms of access with the expansion of these retail clinics, and document important patterns of over-prescription with potentially negative consequences due to increased bacterial resistance. Understanding the downside to private-market innovations in healthcare is crucial as they expand.

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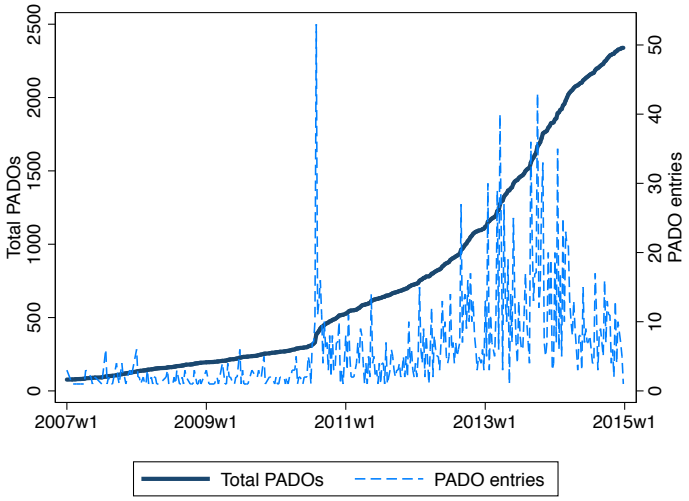
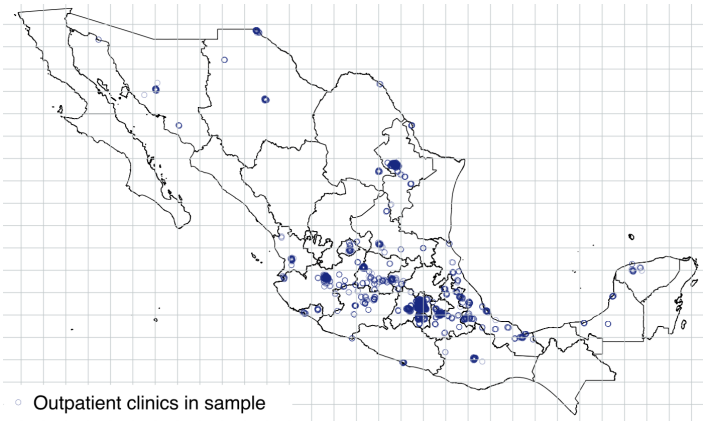
Figures and Tables

Figure 1:
PADO Entry and Accumulated PADOs



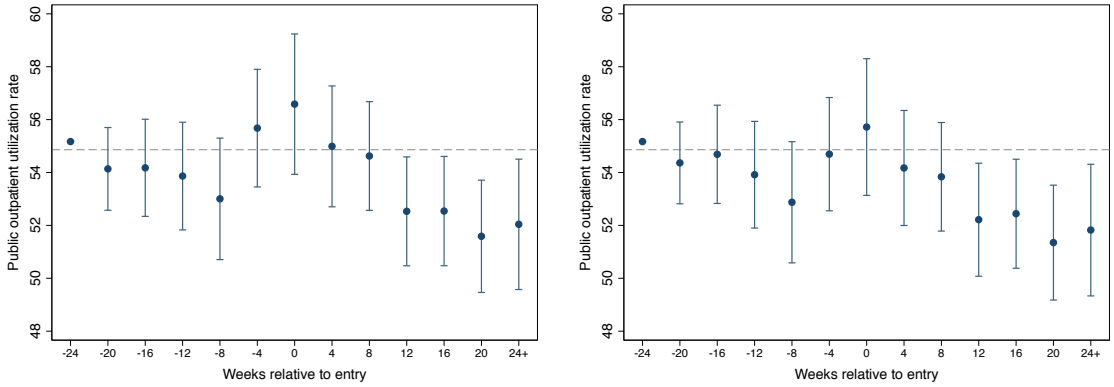
Notes: This graph plots the country-level PADO entries observed in the COFEPRIS dataset on a weekly basis from 2007 to 2014, as well as the cumulative count of PADOs.

Figure 2:
Spatial Distribution of Outpatient Clinics in Sample



Notes: This map shows the location of the 2,260 outpatient clinics in the analysis sample. Grid lines correspond to latitude and longitude degrees.

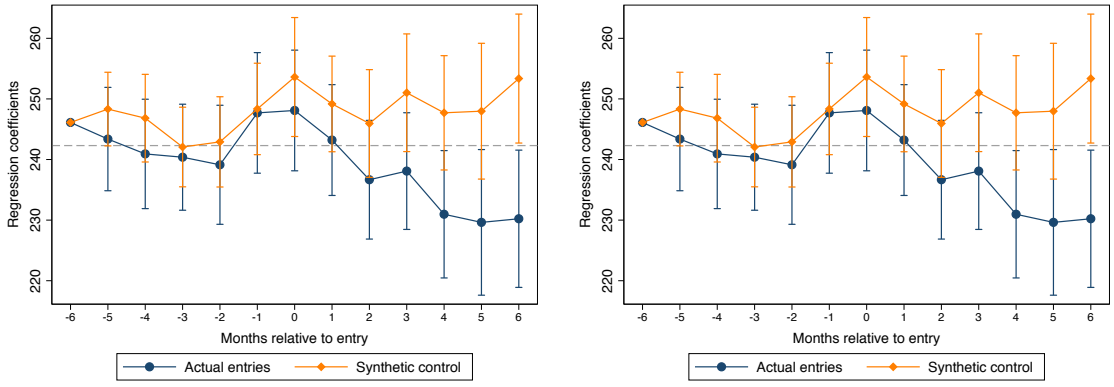
Figure 3:
First PADO Entry and Outpatient Utilization Rates



(a) Main specification (b) Regional trends

Notes: These plots show the effect of the first PADO entry in a public outpatient clinic's catchment area on the utilization rate of clinic services, from a total of 2,260 entry events. The graphs show the coefficients from regressing utilization rates on a vector of leads and lags of first PADO entry, with clinic catchment area and week-year fixed effects (see equation 1 in text). Standard errors are clustered at the catchment area level, and 95% confidence bars are shown. Dashed lines show the sample mean of the dependent variable across observations throughout the 24 weeks prior to entry. Each series is shifted by a constant so that the mean of the regression coefficients is equal to the sample mean of the dependent variable. Figure 3a corresponds to the main specification, while Figure 3b also includes regional trends (latitude-longitude grid cell by month fixed effects).

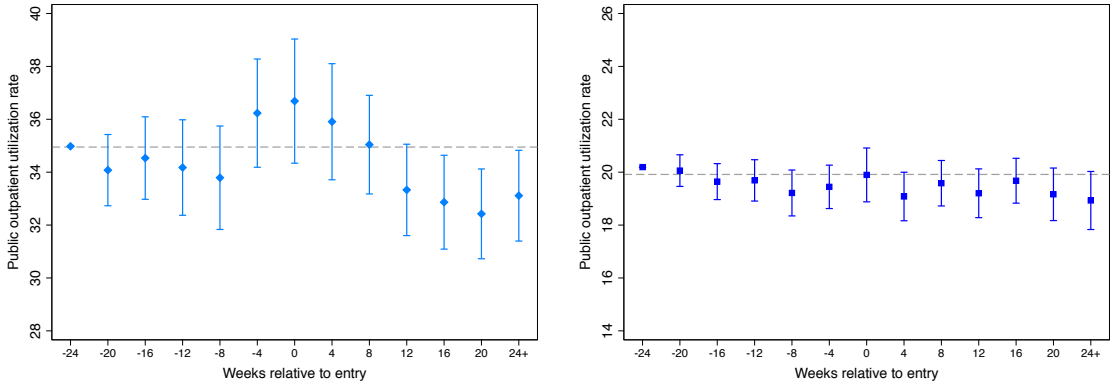
Figure 4:
Synthetic Control Exercise for the Effect of First PADO Entry on
Public Outpatient Utilization Rates



(a) Main specification (b) Regional trends

Notes: These plots show the main effect on treated public outpatient clinics, as well as the estimates for a group of synthetic controls (2,260 controls, one for each treated unit; see text for more details). The graphs show the coefficients from regressing utilization rates on a vector of leads and lags of first PADO entry, with clinic catchment area and month-year fixed effects (see equation 1 in text). Standard errors are clustered at the catchment area level, and 95% confidence bars are shown. Dashed lines show the sample mean of the dependent variable across observations in the original treated clinics throughout the 24 weeks prior to entry. Each series is shifted by a constant so that the mean of the regression coefficients is equal to the sample mean of the dependent variable. Figure 4a corresponds to the main specification, while Figure 4b also includes regional trends (latitude-longitude grid cell by month fixed effects).

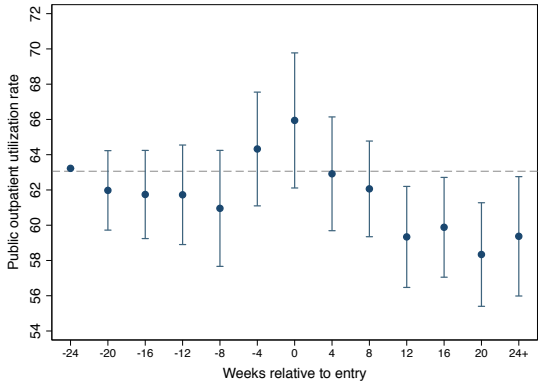
Figure 5:
First PADO Entry and Outpatient Utilization Rates by Diagnosis



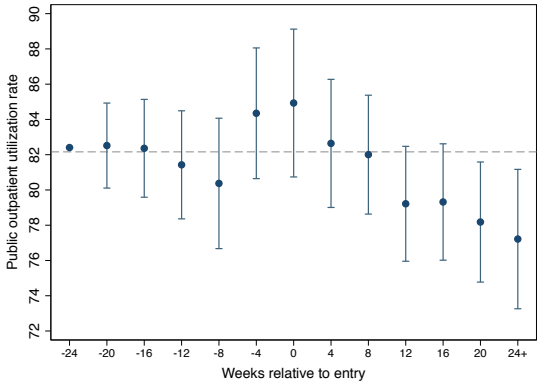
(a) ARIs only (b) Non-ARIs

Notes: These plots show the effect of the first PADO entry in a public outpatient clinic's catchment area on the utilization rate of clinic services by diagnosis, from a total of 2,260 entry events. The graphs show the coefficients from regressing utilization rates on a vector of leads and lags of first PADO entry, with clinic catchment area and week-year fixed effects (see equation 1 in text). Standard errors are clustered at the catchment area level, and 95% confidence bars are shown. Dashed lines show the sample mean of the dependent variable across observations throughout the 24 weeks prior to entry. Each series is shifted by a constant so that the mean of the regression coefficients is equal to the sample mean of the dependent variable. Figure 5a restricts to ARI diagnoses, while Figure 5b shows the remaining diagnoses.

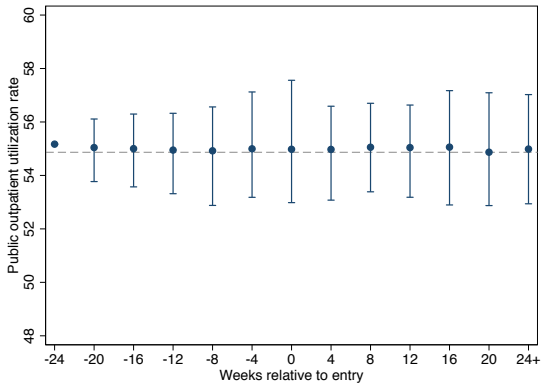
Figure 6:
Robustness Checks for the Effect of First PADO Entry on
Outpatient Utilization Rates



(a) Sufficiently isolated events



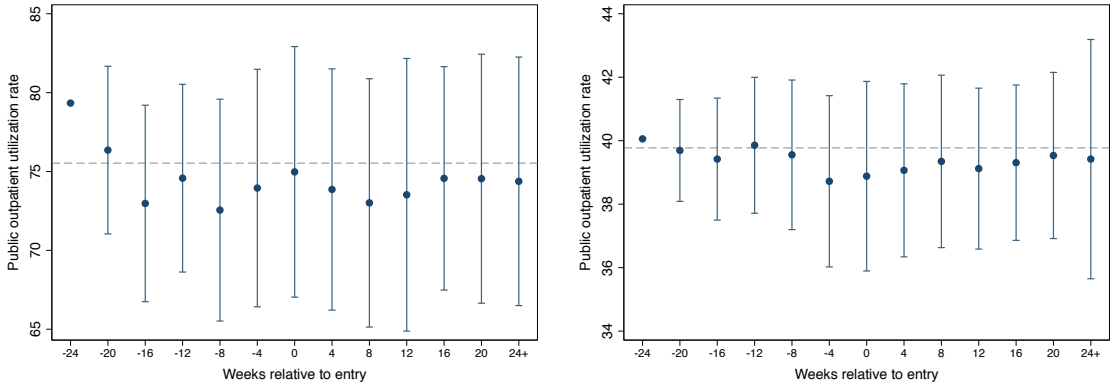
(b) Clinics with non-zero registered cases



(c) Placebo check with a random date

Notes: These plots show the results of different robustness checks on the main result. The graphs show the coefficients from regressing utilization rates on a vector of leads and lags of first PADO entry, with clinic catchment area and week-year fixed effects (see equation 1 in text). Standard errors are clustered at the catchment area level, and 95% confidence bars are shown. Dashed lines show the sample mean of the dependent variable across observations throughout the 24 weeks prior to entry. Each series is shifted by a constant so that the mean of the regression coefficients is equal to the sample mean of the dependent variable. Figure 6a restricts the sample to events where the second observed PADO entry occurs at least 25 weeks after the first entry (1,463 events). Figure 6b restricts the sample to clinics that have a positive number of weekly cases within 24 weeks of entry on either side (1,296 events). Figure 6c shows the results of a placebo exercise, assigning a randomly chosen entry date from the pool of all actual entry dates to each of the original 2,260 clinics. The average of estimated coefficients over 100 iterations are shown, with a 90% confidence interval.

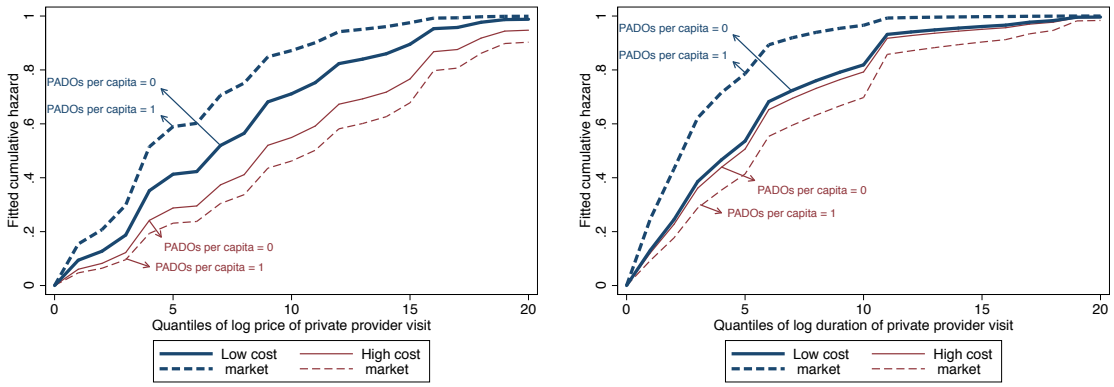
Figure 7:
First PADO Entry and Inpatient Utilization & Hospitalization Rates



(a) Public inpatient services (b) Admissions at SSA hospitals

Notes: These plots show the effect of the first PADO entry on the utilization rate of inpatient services and on the hospitalization rate at SSA hospitals. The graphs show the coefficients from regressing utilization rates on a vector of leads and lags of first PADO entry, with clinic catchment area and week-year fixed effects (see equation 1 in text). Standard errors are clustered at the catchment area level, and 95% confidence bars are shown. Dashed lines show the sample mean of the dependent variable across observations throughout the 24 weeks prior to entry. Each series is shifted by a constant so that the mean of the regression coefficients is equal to the sample mean of the dependent variable. Figure 7a corresponds to inpatient services at public hospitals, for 386 entry events. Figure 7b refers to hospitalizations at SSA hospitals, for 254 events.

Figure 8:
Estimated Distributional Effect of PADOs on Service
Characteristics of Traditional Private Providers



(a) Price of private doctor visit (b) Time spent with patient

Notes: These plots show estimated cumulative distribution functions (CDFs) for the price of private doctor visits and the duration of private doctor consultations, following a hazard model (see text for more details). Both graphs distinguish between the low-cost and high-cost private market, and between the estimated CDF for markets without PADOs and with one PADO per 100,000 people. The left graph shows the full estimated CDF for paying at each quantile of the natural log of the price. The graph on the right shows the CDF for visit durations at each quantile of the natural log of the time private doctors spend with patients. For reference, quantiles 5, 10, 15, and 20 correspond to 99, 200, 403, and 2,500 pesos for the graph on the left, and to 15, 20, 30, and 60 minutes for the graph on the right.

Table 1:
Descriptive Statistics of Public Clinic Catchment Areas and PADO Entry

Panel A: Public Outpatient Clinics	Clinics in sample	Rest of clinics
All new diagnoses per 100,000	54.20	114.73***
	(127.09)	(283.37)
ARI diagnoses per 100,000	34.75	72.37***
	(86.82)	(190.37)
Fraction IMSS	0.16	0.05***
	(0.37)	(0.21)
Fraction SSA	0.68	0.67
	(0.47)	(0.47)
Fraction IMSS-Oportunidades	0.07	0.25***
	(0.26)	(0.43)
Fraction ISSSTE	0.06	0.03***
	(0.23)	(0.16)
Fraction other local government	0.03	0.01***
	(0.16)	(0.08)
Total exam rooms, 2014	6.85	1.69***
	(9.52)	(2.17)
Total doctors, 2014	12.67	2.39***
	(21.60)	(5.03)
PADOs in catchment area, 2008 week 1	1.02	
	(1.79)	
PADOs in catchment area, 2013 week 52	13.44	
	(15.71)	
Total PADOs entering catchment area, yearly	1.56	
	(13.83)	
Weeks featuring entry, yearly	1.12	
	(7.55)	
Total public outpatient clinics	2,260	14,259
Observations	940,160	5,931,744

Panel B: PADO Entries	First observed entry	Subsequent entries
Fraction with more than one entrant	0.11	0.20***
	(0.31)	(0.40)
Number of entrants	1.23	1.41***
	(1.03)	(1.19)
Weeks until next observed entry	43.89	13.31***
	(46.42)	(20.35)
Observations	2,260	17,970

Notes: This table shows summary statistics for public outpatient clinic catchment areas and PADO entries. Means shown, with standard deviations in parentheses. Significance of difference in means test shown between columns. For Panel A, clinics in the sample are the ones for which I observe a first PADO entry between 2008 and 2013 within its 5 kilometer catchment area in the COFEPRIS data. For Panel B, observed entries are divided into first entry and subsequent entries.
*** p<0.01, ** p<0.05, * p<0.1

Table 2:
DD Effect on Types of Outpatient Care

	PADO (1)	Non-PADO (2)	Traditional Private (3)	Public (4)	All Outpatient (5)
Panel A: All illnesses					
PADO counts per 100,000	0.028**	-0.091***	-0.040	-0.051	-0.063*
	(0.014)	(0.035)	(0.025)	(0.033)	(0.034)
Observations	48,753	48,753	48,753	48,753	48,753
R-squared	0.056	0.039	0.041	0.047	0.036
Mean dependent variable	0.028	0.298	0.094	0.204	0.326
Panel B: ARIs					
PADO counts per 100,000	0.038**	-0.083**	-0.046	-0.037	-0.044
	(0.015)	(0.037)	(0.033)	(0.043)	(0.040)
Observations	24,579	24,579	24,579	24,579	24,579
R-squared	0.078	0.062	0.066	0.074	0.063
Mean dependent variable	0.035	0.248	0.083	0.165	0.282
Panel C: GIDs					
PADO counts per 100,000	-0.024	-0.171	-0.034	-0.137	-0.194
	(0.066)	(0.153)	(0.117)	(0.087)	(0.158)
Observations	2,737	2,737	2,737	2,737	2,737
R-squared	0.249	0.288	0.279	0.288	0.285
Mean dependent variable	0.037	0.322	0.117	0.205	0.359
Panel D: Chronic diseases					
PADO counts per 100,000	0.002	-0.048	0.021	-0.069	-0.046
	(0.028)	(0.123)	(0.078)	(0.121)	(0.125)
Observations	3,340	3,340	3,340	3,340	3,340
R-squared	0.272	0.246	0.223	0.241	0.243
Mean dependent variable	0.015	0.399	0.081	0.319	0.414

Notes: This table shows the estimates from regressing an indicator for type of care conditional on being sick on PADO counts per capita (see equation 2 in text for more details). All regressions include municipality fixed effects, an indicator for the survey year, pharmacies per capita at the municipality level and its square, age, gender, and dwelling indicators for having a dirt floor, electricity, piped water, and sewage. Robust standard errors in parentheses, clustered at the municipality level. Each panel focuses on a different type of illness.
*** p<0.01, ** p<0.05, * p<0.1

Table 3:
Descriptive Statistics Penicillin Sales Data

	All Local Urban Markets			Only Markets with PADOs			
	Units Sold	Average Price	Observations	Units Sold	Average Price	Observations	Share of Total
All Penicillins	10.19	108.96		18.16	111.23		
	(143.18)	(25.55)	4,209,120	(152.40)	(24.32)	1,684,980	1.00
Generic Penicillins	7.22	34.93		14.04	39.07		
	(72.01)	(13.04)	1,706,400	(109.22)	(11.58)	683,100	0.41
Brand-Name Penicillins	12.21	137.66		20.97	143.42		
	(175.87)	(24.16)	2,502,720	(175.81)	(23.96)	1,001,880	0.59
Basic Aminopenicillins	9.15	82.01		15.62	80.78		
	(161.63)	(19.94)	2,980,512	(163.34)	(17.76)	1,193,148	0.71
Combination Penicillins	12.71	163.78		24.32	163.40		
	(82.73)	(39.18)	1,228,608	(121.64)	(35.28)	491,832	0.29
Generic Basic Aminopenicillins	5.89	30.16		11.09	33.61		
	(63.65)	(11.96)	1,387,872	(95.82)	(10.71)	555,588	0.33
Brand-Name Basic Aminopenicillins	11.99	103.62		19.57	103.50		
	(212.94)	(16.90)	1,592,640	(204.68)	(15.46)	637,560	0.38
Generic Combination Penicillins	13.02	49.45		26.88	52.50		
	(100.42)	(16.75)	318,528	(153.94)	(15.19)	127,512	0.08
Brand-Name Combination Penicillins	12.60	198.75		23.42	203.23		
	(75.56)	(33.73)	910,080	(108.06)	(30.76)	364,320	0.22

Notes: This table shows summary statistics calculated from the penicillin sales dataset from 2010 to 2012. Observations are at the month-market-product level. Means for each variable, with standard deviations shown in parentheses. Each sample consists of 36 months and 185 products. The full sample in the first three columns contains 632 local urban markets. The sample in the last three columns corresponds to 253 local urban markets that have PADOs in this time period according to the COFEPRIS data. The average price is weighted by local sales volume.

Table 4:
PADOs and Unit Sales of Penicillins by Categories

	(1)	(2)	(3)	(4)	(5)
Total PADOs per 100,000 × basic × generic	-0.386	0.038	-0.386	-0.333	-0.379
	(0.276)	(0.081)	(0.278)	(0.246)	(0.300)
Total PADOs per 100,000 × basic × brand	-0.222	-0.601***	-0.222	-0.169	-0.078
	(0.173)	(0.145)	(0.171)	(0.192)	(0.190)
Total PADOs per 100,000 × complex × generic	1.207***	1.851***	1.207***	1.260***	0.846**
	(0.298)	(0.268)	(0.298)	(0.310)	(0.328)
Total PADOs per 100,000 × complex × brand	0.592***	0.383***	0.592***	0.645***	0.530***
	(0.145)	(0.094)	(0.143)	(0.182)	(0.152)
Observations	4,209,120	4,209,120	4,209,120	4,209,120	1,684,980
R-squared	0.019	0.622	0.019	0.020	0.021
Clusters	632	116,920	632	632	253
Mean dependent variable by type:					
Basic generic	3.08	3.08	3.08	3.08	3.76
Basic brand	5.80	5.80	5.80	5.80	6.27
Complex generic	5.49	5.49	5.49	5.49	8.00
Complex brand	5.59	5.59	5.59	5.59	7.03
Local urban market LUM FE	X		X	X	X
LUM × product FE		X			
Lat.-lon. cell × month FE			X		
Quadratic trend by LUM				X	
Excluding zero PADOs					X

Notes: This table shows how penicillin sales change with PADO presence. Observations are at the penicillin product, local urban market (LUM), month-year level. The estimates come from regressing unit sales per 100,000 on PADO counts per 100,000, time and LUM fixed effects (see equation 3 in text). Robust standard errors in parentheses, clustered at the LUM or LUM×product level (column 3).
*** p<0.01, ** p<0.05, * p<0.1

Table 5:
PADOs and Average per Unit Price of Penicillins

	(1)	(2)	(3)	(4)
Total PADOs per 100,000	-1.337**	-1.306**	-1.497**	-1.744***
	(0.572)	(0.544)	(0.665)	(0.617)
Observations	22,258	22,258	22,258	8,973
R-squared	0.645	0.659	0.753	0.703
Clusters	627	627	627	253
Mean dependent variable	109.0	109.0	109.0	111.2
Local urban market LUM FE	X	X	X	X
LUM × product FE				
Lat.-lon. cell × month FE		X		
Quadratic trend by LUM			X	
Excluding zero PADOs				X

Notes: This table shows how the average penicillin price per unit changes with PADO presence. Observations are at the local urban market (LUM), monthly date level. The estimates come from regressing average price on PADO counts per 100,000, date and LUM fixed effects (see equation 3 in text). Robust standard errors in parentheses, clustered at the LUM.
*** p<0.01, ** p<0.05, * p<0.1

Table 6:
Private and Public Market Responses to PADOs

1. Private market response

			Segmented by true median cost				Segmented by predicted median cost			
	Full sample		Below median		Above median		Below median		Above median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Cost of private doctor visit										
PADO counts per 100,000	-0.284	-0.229	-0.410***	-0.363**	0.063	0.037	-0.770**	-0.719*	0.321	0.312
	(0.217)	(0.217)	(0.145)	(0.153)	(0.114)	(0.113)	(0.381)	(0.382)	(0.334)	(0.346)
Observations	2,223	2,223	980	980	1,243	1,243	682	682	682	682
R-squared	0.029	0.034	0.015	0.026	0.030	0.034	0.019	0.024	0.006	0.009
Municipality controls		X		X		X		X		X
Panel B: Duration of private doctor visit										
PADO counts per 100,000	0.040	0.058	-0.177	-0.202	0.184	0.215	-0.403*	-0.357	0.469**	0.452**
	(0.117)	(0.118)	(0.199)	(0.199)	(0.132)	(0.131)	(0.212)	(0.218)	(0.225)	(0.215)
Observations	2,604	2,604	978	978	1,626	1,626	681	681	680	680
R-squared	0.002	0.004	0.018	0.023	0.003	0.005	0.015	0.036	0.010	0.012
Municipality controls		X		X		X		X		X

2. Public market response

	Duration of visit		Waiting times	
	(11)	(12)	(13)	(14)
PADO counts per 100,000	-0.035	-0.026	0.129	0.159
	(0.065)	(0.066)	(0.183)	(0.182)
Observations	8,388	8,388	8,388	8,388
R-squared	0.006	0.010	0.006	0.007
Municipality controls		X		X

Notes: This table shows the estimates from regressing each outcome on PADO counts per capita for the 2012 ENSANUT. Regressions include controls for pharmacies per capita at the municipality level and its square, age, gender, and dwelling indicators for having a dirt floor, electricity, piped water, and sewage. Municipality controls are municipality averages of the dwelling indicators. Robust standard errors in parentheses, clustered at the municipality level. The first section of the table considers responses for the private market (price and duration of visit), while the second section considers the public healthcare market (duration of visit and waiting times). All outcomes are in natural logs. Columns 3-6 divide the sample by the median of the observed natural log of the cost of private doctor visits. Columns 7-10 divide the sample based on the median of the predicted cost (see text for more details).
*** p<0.01, ** p<0.05, * p<0.1

Appendices for Online Publication

A The Mexican Healthcare System

Healthcare in Mexico is provided by both a public and private sector. The public sector is divided into two main institutions, with their own separate set of providers. Formal workers, their dependents, retirees, and anyone voluntarily contributing to the system have access to IMSS (*Instituto Mexicano del Seguro Social* or Mexican Social Security Institute). On the other hand, informal workers, self-employed, and unemployed individuals have access to healthcare through enrollment in *Seguro Popular* (SP), which is administered by the Ministry of Health (SSA).[1]

Additionally, state workers (ISSSTE), workers of the national oil company (PEMEX), the Ministry of Defense (SEDENA), and the Marines (SEMAR) each maintain a separate public system, with different providers and benefit plans. The largest of these complementary institutions is ISSSTE.

Private insurance is mostly employment-based but only at higher wage levels, and serves as a complement to the legal requirement of enrollment in IMSS.[2] This type of insurance can only be used with private providers.

Healthcare providers for the public system are the hospitals, clinics, and doctors that belong to each of these institutions. They are financed by a mix of contributions from the government, employers, and workers. The cost of enrolling in SP is determined by household income decile, with the annual household fee capped at around 6,000 pesos (about 353 USD). There is generally very low portability of benefits from one public system to the other, and

[1] Before the creation of SP, any individual not affiliated with IMSS (and unable to pay for private healthcare, either out of pocket or through insurance), had access to SSA hospitals, clinics, and doctors. Nowadays, SSA provides health services to both SP affiliates and unaffiliated individuals, who are usually just enrolled on the spot.

[2] Evidently, private insurance can also be purchased independently by individuals.

benefit plans vary substantially across institutions. Although in theory individuals may not enroll in more than one public institution, there are some who actually do.

Table A1 shows insurance coverage as reported in the 2012 ENSANUT. About 73% of the population has access to the public system, with the majority corresponding to IMSS and SSA. Less than 1% of the population has private insurance, and about 26% is uninsured. Note that less than 2% has multiple insurance, which may be a private and public mix or affiliation to more than one public institution.

The 2012 ENSANUT asks respondents to name their main primary healthcare provider. The corresponding summary statistics are shown in Table A1. Around 72% reports public providers as their main source of primary care. There is a sizable percentage for private providers, with 10% at PADOs and 15% at other private providers. Lastly, around 2% reports self-medicating or not getting medical attention.

Actual utilization rates are reported in Table A2. These statistics refer to actual outpatient service utilization during the respondent's last sickness spell, conditional on having been sick and seeking medical attention in the two weeks prior to the survey. Regardless of the symptoms, 58% sought medical attention in the public system, while 15% went to a PADO and 23% to a private clinic, hospital or doctor's office. This shows that in practice there is a large utilization of private health services in Mexico. Table A2 also shows these statistics restricting to respiratory symptoms, gastrointestinal symptoms, and the rest.

Table A3 presents descriptive statistics based on utilization of public, PADO and private outpatient services. Focusing on PADO users, note that 59% reported having respiratory symptoms, compared to only 29% of public sector users. In terms of the reason reported for provider choice, affiliation is the primary reason for seeking attention at a public outpatient clinic. For PADOs, distance and cost are the two most important reasons, while knowing the provider and being satisfied with the quality of care provided are the main reasons for choosing private doctors.

In terms of characterizing visits, transportation costs in time and money are indeed lower for PADOs. They also exhibit the lowest waiting times and duration of consultation. Note that PADO waiting times are around a quarter of the average wait at public institutions, and that private doctors are the ones that spend the most time with patients (about 25% more than public physicians and 60% more than PADO doctors). PADOs are much cheaper than private doctors, at an average cost of 14% of a private consultation. PADO doctors do prescribe the most medications, although the difference with public and private providers is not that large.

The public system also provides medication through their own pharmacies, but supply shortages and long waiting times imply that most medicines are bought out of pocket (around 80% according to the 2012 ENSANUT), even after utilizing outpatient services at one of these institutions.[3] In terms of cost per medication prescribed, private doctors are the most expensive, while the difference between the public sector and PADOs is not large (last two columns of Table A3).

[3]In a literature overview of medicine use in Mexico between 1990 and 2004, Wirtz et al. (2008) argues that frequent drug stock shortages in public health centers are one of the largest issues in the Mexican public health system.

Table A1:
Insurance Coverage and Primary Healthcare Providers

Insurance coverage (affiliation)	
Public insurance	73.34%
Public insurance with IMSS	30.41
Public insurance with SSA	37.57
Private insurance	0.65
Uninsured	25.60
Multiple insurance/affiliations	1.91
Main primary healthcare provider	
Public providers	71.63%
PADOs	10.38
Private providers	15.05
Self-medication	0.42
None/Does not get medical attention	1.36
Total observations	194,923

Notes: This table shows summary statistics of insurance coverage in Mexico, calculated from the 2012 ENSANUT, using survey weights. The first part of the table shows the percentage of respondents reporting insurance coverage by type of provider, and the second half shows the percentage reporting each type as their main primary healthcare provider.

Table A2:
Descriptive Statistics of Utilization Rates by Symptom Type

	Respiratory	Gastro-intestinal	Other	All symptoms
Got care at a public clinic/hospital	0.47	0.47	0.67	0.58
Got care at PADO	0.24	0.21	0.08	0.15
Got care at a private clinic/hospital	0.25	0.27	0.21	0.23
Total observations	4,649	688	7,850	13,187

Notes: This table shows summary statistics of actual utilization, calculated from the 2012 ENSANUT, using survey weights. Statistics are the fraction of respondents that received care at each provider conditional on the type of symptoms reported. All results are conditional on having received medical attention in the two weeks prior to the 2012 ENSANUT.

Table A3:
Descriptive Statistics by Provider Type

	Public	PADO	Private
Patient characteristics			
Female	0.62	0.56	0.58
Age	34.97	21.85	28.32
Poor	0.22	0.15	0.17
Urban	0.76	0.88	0.82
Type of symptoms			
Respiratory symptoms	0.29	0.59	0.41
Gastrointestinal symptoms	0.04	0.08	0.06
Reason for choice			
Affiliation/beneficiary	0.75	0.00	0.03
Provider is near	0.16	0.34	0.17⊛
Provider is cheap	0.16	0.35	0.05
Provider is fast	0.02	0.28	0.22
Know provider	0.02	0.08	0.29
Like quality of care	0.07	0.17	0.28
Visit characteristics			
Transportation cost	25.90	17.35	49.21
	(8,410)	(1,624)	(2,581)
Transportation time	27.11	15.85	25.08
	(8,379)	(1,621)	(2,575)
Waiting time	78.48	19.84	24.06
	(8,391)	(1,623)	(2,593)
Duration of consultation	22.04	17.46	27.49
	(8,356)	(1,626)	(2,596)
Cost of consultation	11.17	39.39	268.77
	(8,420)	(1,626)	(2,597)
Number of medications prescribed	2.63	2.99	2.70*
	(8,412)	(1,622)	(2,607)
Cost of medications	144.85	198.78*	441.22
	(761)	(62)	(74)
Total observations	8,430	1,627	2,612

Notes: This table shows summary statistics (means) for each provider type, calculated from the 2012 ENSANUT, using survey weights. For patient characteristics, types of symptoms, and reason for provider choice, observations correspond to the total observations reported at bottom of table. For visit characteristics, observations for each variable are reported in parentheses. Significance tests of the difference in means performed for PADO and private providers relative to public providers.
All differences in means are significant at the 1% level unless otherwise noted. * $p<0.1$, ⊛ $p>0.1$

B Validating the cofepris Data

The COFEPRIS dataset has almost 2,400 PADOs, while a consulting firm hired by COFEPRIS states in a report that there were 15,000 PADOs at the end of 2014. Figure B2 plots the evolution over time of the PADOs as reported by this consulting firm from 2002 to 2016. Note how the growth rate drastically increases in 2010, but then gradually subsides.

I obtained a copy of this report's main results directly from COFEPRIS. As of August 2017, this report does not seem to be available online. However, the media has reported on these numbers. See for example, http://www.proceso.com.mx/363587/cofepris-sin-capacidad-para-revisar-consultorios-en-farmacias, accessed August 2017.

I first perform a simple back of the envelope calculation that puts the true number of PADOs somewhere between 6,000 and 10,000 in 2014:

1. The report states that the second largest chain, *Farmacias del Ahorro*, has 19% of all PADOs, or 2,400 PADOs by the end of 2014. For this chain, industry and newspaper articles state that there were 1,300 pharmacies in 2016 (see for example, http://www.eluniversal.com.mx/articulo/cartera/negocios/2015/09/4/farmacias-del-ahorro-busca-dar-la-batalla-al-dr-simi). For 2017, I scraped their website for a full roster of 1,441 pharmacies in April 2017. Keeping this growth rate constant and projecting back, I impute 1,058 pharmacies in 2014, which is well below the 2,400 PADOs the report claims. If 19% is the share of *Farmacias del Ahorro* PADOs in 2014, and there were 1,058 such pharmacies, this would imply around 5,600 PADOs in 2014.

2. The report also states that the largest chain, *Farmacias Similares*, has 35% of all PADOs, or 5,250 by the end of 2014. Data directly from their website indicates the existence of 5,176 locations by the end of 2014. However, it is unclear whether these numbers reflect only locations in Mexico, or whether locations in Guatemala and Chile are also included (this international expansion began in 2003). Newspaper reports from the end of 2014, claim instead 3,775 locations for *Farmacias Similares* (see

for example http://eleconomista.com.mx/mercados-estadisticas/2014/12/02/compra-farmacon-sin-efecto-femsa, accessed August 2017). Under the same calculation as above, this would mean around 10,800 PADOs in 2014.

3. Adding both of these pharmacy numbers together, the report claims they represent 54% of all PADOs. Since by late 2014, they jointly had 4,800 locations, this implies that the true number of PADOs would be around 8,900.

This exercise shows that the 15,000 PADOs claimed by the consulting firm are clearly an overestimate of the true number. However, the almost 2,400 counts in my COFEPRIS data are still considerably less than even the most optimistic calculations. As such, I validate the reliability of these data using two methods. First, I use survey data to show that my counts are a good predictor of reported PADO use. Second, I obtain manual counts for a subsample of areas and compare directly with the COFEPRIS counts.

B.1 Survey Data

Using the National Health Survey (ENSANUT), I validate the PADO counts dataset obtained from COFEPRIS by showing that these counts are a good predictor of reporting PADO use in the survey.

There are two rounds of the ENSANUT: 2006 and 2012. In 2006, PADOs were not a widespread phenomenon. According to the COFEPRIS dataset, there were only 52 PADOs in the entire country in January 2006. By January 2012, they had increased to 753. This expansion coincides with the introduction of a law limiting over-the-counter access to antibiotics in August 2010.

The 2006 ENSANUT does not ask individuals whether they got medical attention when sick at a PADO, precisely because it was not a common occurrence. However, in the 2012 round, PADO care is included.

I estimate the following equation:

$$PADOcare_{imy} = \beta(\Delta PPC_m \times \mathbb{1}_{[y=2012]}) + X_{imy}\gamma + \theta_m + \lambda_y + \varepsilon_{imy} \quad \text{(B1)}$$

where $\Delta PPC_m = PPC_{m,2012} - PPC_{m,2006}$ is the change in PADO counts per capita from 2006 to 2012 according to the COFEPRIS dataset, $\mathbb{1}_{[y=2012]}$ is an indicator for being in the 2012 survey, θ_m are municipality fixed effects, λ_y are survey year indicators, and X_{imy} is a vector of controls at the individual and municipality level.

The coefficient β indicates by how much the probability of choosing PADO care changes from 2006 to 2012 in places where the PADO counts per capita increased relative to those where there was no change (i.e., where there are no PADOs). Note that because in 2006 nobody reports going to a PADO, these coefficients should be very similar to a simple cross-sectional analysis of 2012.

Table B1 presents the estimates for equation B1. Column 1 only includes municipality fixed effects and survey year indicators, while columns 2 to 4 gradually add controls. The estimate is positive, significant and similar in magnitude across all specifications.

Overall, these results suggest that although the COFEPRIS counts may be a noisy measure of the true PADO counts, they are a good predictor of getting care at a PADO in the survey data.

B.2 Manual Counts

To get a better grasp of the missing PADOs in the COFEPRIS data, I obtain a manual count of PADOs using Google Maps.

In the main results in the paper, I consider catchment areas as circles with a 5 km radius around public outpatient clinics. This yields 2,260 catchment areas with at least one PADO entry in the COFEPRIS data for the 2007-2014 period. Here, I restrict to 1 km radius

catchment areas (the results for which are also part of the robustness checks and are available upon request). This leaves me effectively with 1,069 catchment areas.

For these catchment areas, I randomly choose a total of 15 or 1.4% of the total. I then use Google Maps to identify the total number of PADOs in this area as of July 2017. The procedure is as follows. First, I use the clinic's geographic coordinates to draw a 1 km radius in Google Maps. Second, I do a nearby search for *farmacia* and *farmacias* since most pharmacies include these words in their name. Third, I verify that these pharmacies have a PADO either by Google searches or using the street-view tool. Fourth, I verify that the PADOs in my COFEPRIS data are actually shown in the map. Finally, I do a zoomed in visual inspection to identify potential PADOs that did not appear in the nearby search.

Note that the PADO counts in the COFEPRIS only extend to December 2014. Therefore, the manual PADO counts may overestimate the true counts in December 2014. Determining the opening date of each PADO is a difficult task. Over this period, there is an expansion in both PADOs and pharmacies. Directly contacting pharmacy staff over the phone did not yield consistent results, and this particular approach may lack reliability. Additional checks using local newspapers and telephone books online were also unsuccessful.

Figure B1 shows the scatterplot for the true number of PADO counts obtained from Google Maps and the number in the COFEPRIS data for each of the 15 catchment areas analyzed here. The size of the markers represents how many catchment areas have that particular combination of true and observed PADOs. The 45 degree line is also shown. Note how there is a strong correlation between real and observed PADOs.

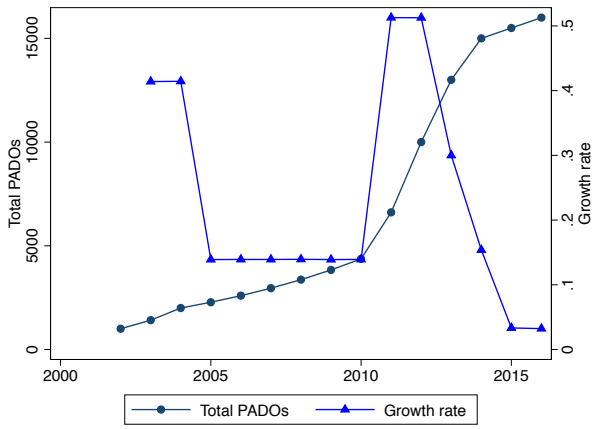
Figure B3 shows the same plot for the true number of PADOs and the number of missing PADOs, which is just the difference between the manual counts and the observed counts. This plot shows that the missing data does not correlate with the true number of PADOs. Additionally, Figure B4 shows the distribution of the number of missing PADOs.

Table B2 shows the relationship between the missing PADOs and the true counts. The first three columns show that the number of missing PADOs in a catchment area is not

well-predicted by the true number of PADOs, the area's population, and the clinic's public subsystem affiliation. The last column shows the positive correlation between the true counts and the COFEPRIS data.

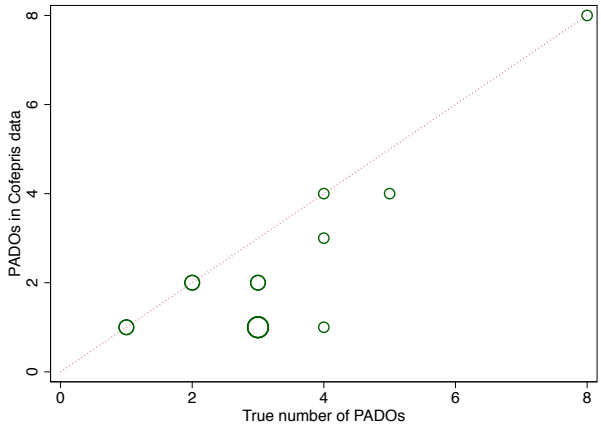
Lastly, Table B3 considers each of the 49 true PADOs in these 15 catchment areas, using an indicator for being absent in the COFEPRIS data as the outcome variable. The main set of explanatory variables refer to the pharmacy chain that each PADO belongs to. Column 1 controls for catchment area characteristics, and column 2 includes catchment area fixed effects. Both columns show that the probability of missing an independent pharmacy PADO is much greater than missing one belonging to the five largest chains (*Ahorro*, *Similares*, *Guadalajara*, *Benavides* and *GI*).

Figure B1:
Evolution of PADOs over time according to consulting firm document



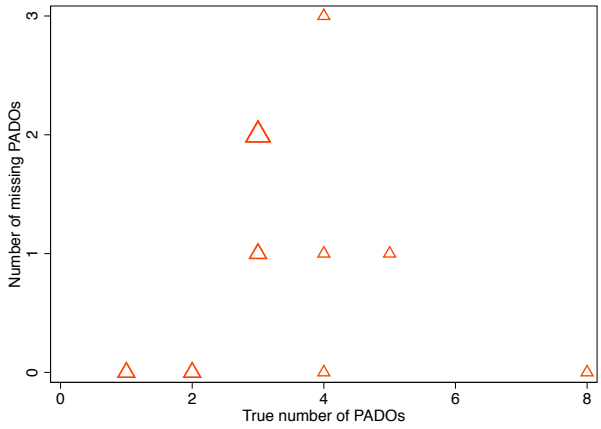
Notes: This graph plots the number of PADOs and the yearly growth rate according to the numbers presented by the consulting firm to COFEPRIS. The data from 2002 to 2014 is available directly through that document. A shorter, incomplete version is available at http://www.cofepris.gob.mx/Documents/NotasPrincipales/12022015.pdf, accessed February 2017. The data for 2016 comes from media reports, such as http://www.noticiasmvs.com/#!/noticias/llaman-autoridades-sanitarias-a-la-industria-farmaceutica-a-sumarse-al-combate-de-la-obesidad-y-la-diabetes-585, accessed August 2017. Data for 2015 is imputed.

Figure B2:
True PADO counts vs COFEPRIS data in catchment areas



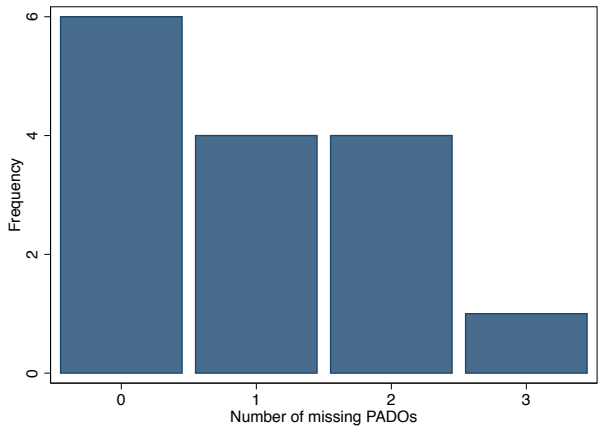
Notes: This graph plots the true number of PADOs against the number observed in the COFEPRIS data for 15 randomly chosen catchment areas (1 km radius). The true counts correspond to data in July 2017, while the COFEPRIS data corresponds to December 2014. The size of the markers represents the number of catchment areas with each true-observed combination. The 45 degree line is shown for reference.

Figure B3:
True PADO counts vs missing counts in catchment areas



Notes: This graph plots the true number of PADOs against the number of missing PADOs (the difference between true counts and those observed in the COFEPRIS data) for 15 randomly chosen catchment areas (1 km radius). The true counts correspond to data in July 2017, while the COFEPRIS data corresponds to December 2014. The size of the markers represent the number of catchment areas with each true-observed combination.

Figure B4:
Distribution of number of missing counts in catchment areas



Notes: This graph shows the distribution of the number of missing PADOs (the difference between true counts and those observed in the COFEPRIS data) for 15 randomly chosen catchment areas (1 km radius). The true counts correspond to data in July 2017, while the COFEPRIS data corresponds to December 2014.

Table B1:
Validating COFEPRIS Data with Survey Data

	(1)	(2)	(3)	(4)
ΔPADO counts per 100,000 × 2012	0.033**	0.030**	0.028**	0.027*
	(0.014)	(0.014)	(0.014)	(0.014)
Observations	48,753	48,753	48,753	48,753
R-squared	0.051	0.051	0.056	0.058
Municipality FE	X	X	X	X
Pharmacies per capita controls		X	X	X
Individual controls			X	X
Individual affiliation controls				X

Notes: This table validates the COFEPRIS dataset by estimating a difference-in-differences equation (as equation 2 in the main text) using survey data from the 2006 and 2012 ENSANUT. The dependent variable is an indicator for choosing PADO care conditional on being sick. Robust standard errors in parentheses, clustered at the catchment area level.
*** p<0.01, ** p<0.05, * p<0.1

Table B2:
Relationship between true PADO counts and missing PADOs

	Number of missing PADOs			True counts
	(1)	(2)	(3)	(4)
True number of PADOs	0.05	0.02	0.13	
	(0.182)	(0.198)	(0.213)	
Population		-0.00	-0.00	
		(0.000)	(0.000)	
SSA catchment area			0.96	
			(1.035)	
IMSS catchment area			1.10	
			(0.960)	
PADOs in COFEPRIS data				0.76***
				(0.092)
Constant	0.84	1.10	-0.09	1.53***
	(0.613)	(0.813)	(1.448)	(0.406)
Mean dependent variable	1.00	1.00	1.00	3.27
Observations	15	15	15	15
R-squared	0.007	0.030	0.126	0.727

Notes: This table analyzes the relationship between true PADO counts and missing PADOs for 15 randomly chosen catchment areas (1 km radius). Observations are at the catchment area level. Columns 1-3 consider the difference between true counts and those observed in the COFEPRIS data as the dependent variable, while column 4 uses the true counts. The true counts correspond to data in July 2017, while the COFEPRIS data corresponds to December 2014. Robust standard errors in parentheses, clustered at the catchment area level.
*** p<0.01, ** p<0.05, * p<0.1

Table B3:
Probability of observing PADOs in the COFEPRIS data

	(1)	(2)
Dr. Descuento pharmacy PADO	-0.56	0.43***
	(0.402)	(0.143)
Ahorro pharmacy PADO	-0.29	0.60***
	(0.321)	(0.153)
Similares pharmacy PADO	-0.17	0.62***
	(0.260)	(0.048)
Guadalajara pharmacy PADO	-0.07	0.76***
	(0.324)	(0.095)
Benavides pharmacy PADO	0.27	0.88
	(0.436)	(0.512)
GI pharmacy PADO	0.44	1.13***
	(0.323)	(0.228)
Independent pharmacy PADO	0.76***	1.73***
	(0.230)	(0.119)
True number of PADOs in catchment area	0.02	
	(0.038)	
Population	-0.00	
	(0.000)	
SSA catchment area	0.36*	
	(0.203)	
IMSS catchment area	0.48*	
	(0.227)	
Mean dependent variable	0.31	0.31
Observations	49	49
R-squared	0.592	0.740
Catchment area FE		X

Notes: This table shows determinants of the probability that a true PADO is observed in the COFEPRIS data. Each observation is a true PADO existing in July 2017, and the dependent variable is an indicator for whether that PADO is observed in the COFEPRIS data by December 2014. The first seven explanatory variables are indicators for different pharmacy chains. Both columns suppress the constant term so that there is no pharmacy chain category excluded. Robust standard errors in parentheses, clustered at the catchment area level.
*** p<0.01, ** p<0.05, * p<0.1

C Potential Bias in the Event Study Design

This appendix simulates data under an event study framework in order to understand potential bias from missing data.

C.1 Setup

Let t denote weekly time periods with $t \in \{1, 2, ..., T\}$, and c denote catchment areas with $c \in \{1, 2, ..., C\}$.

The simulation procedure takes the following five steps:

1. Define the total number of entries J in the simulation. These entries will then be allocated across time and space.

2. Assign entries over time such that the distribution of accumulated entries over time follows the one observed for the entries in the COFEPRIS data.

   Specifically, if $X(t)$ denotes the total accumulated entries by date t in the simulation, then $X(t) = m(X^O(t))$ where $m(\cdot)$ is a local mean smoothing polynomial and $X^O(t)$ are the accumulated entries over time in the COFEPRIS dataset.

3. Randomly assign entries to a catchment area c, such that for any entry in a given date t, the probability of being assigned to a catchment area c is constant at $1/C$.

4. The data generating process (DGP) for the outcome is given by:

$$y_{ct} = \begin{cases} w_{ct} - 0.1X_{ct} + r_{ct} & \text{if } w_{ct} - 0.1X_{ct} + r_{ct} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

   where $w \sim Exp(1.5)$, X_{ct} is the accumulated number of entries at date t in area c, and $r \sim N(0, 0.5)$. Essentially, each additional entry decreases the outcome by 0.1. The choice of the exponential parameter for w and the variance of r are ad hoc and

can be easily modified. Overall, this DGP yields an outcome that follows a similar distribution to the utilization rates actually observed.

5. Choose a subset of the total entries to be the observed entries. Define

$$\Pr(x_{ct} \text{ is observed}) = p$$

where x_{ct} is an entry in area c at time t, and $p = 1/J$.

C.2 Different number of total entries J

Key assumptions:

1. $T = 416$ and $C = 2,000$

   In the actual data, I observe 416 weeks (52 weeks $\times$ 8 years) and around 16,000 catchment areas. Imposing $C = 2,000$ guarantees that it will be more likely that multiple entries appear for a given catchment area.

2. The DGP is as defined in step 4 of the procedure.

   Each additional entry has the same marginal effect on the outcome of 0.1, so that there is no bias from misclassifying the true entry order of an observed first entry.

3. The probability of observing an entry is as defined in step 5 of the procedure.

   The probability of a simulated entry being observed is uniform across all entries.

I run the simulation and estimate a regression of the form:

$$y_{ct} = \beta_{-A}\mathbb{1}_{[t-E_c\leq -A]} + \sum_{d=-A+1}^{B-1} \beta_d \mathbb{1}_{[t-E_c=d]} \quad + \beta_B \mathbb{1}_{[t-E_c\geq B]} + \gamma_t + \theta_c + \varepsilon_{ct} \tag{C1}$$

where the independent variables $\mathbb{1}_{[t-E_c=d]}$ are indicators for weeks around entry (bunched in groups of four), γ_t are date fixed effects, θ_c are catchment area fixed effects, and ε_{ct} is the error

term. I restrict to the first observed entry only. This is the same specification as in the paper.

I repeat this procedure 100 times for:

- $J = 50,000 \longrightarrow$ an overly exaggerated number of entries
- $J = 15,000 \longrightarrow$ the number of entries claimed by a consulting firm in 2014
- $J = 8,000 \longrightarrow$ my back of the envelope calculation of the true entries

Lastly, I plot the average of the coefficients obtained in these simulations, as well as confidence intervals.

Results

Figure C1 shows the total number of PADO entries in the COFEPRIS dataset over time, as well as the accumulated number of PADOs. The same is shown for the simulated entries when $J = 8,000$. Note how the simulated entries follow a similar pattern to the COFEPRIS entries: relatively flat from 2007 to mid-2010, and subsequently a sharp increase in accumulated PADOs. The same holds for other values of J.

Figure C2 shows the distribution of the number of weeks from the first observed entry in a catchment area to the next entry. Each line corresponds to a simulation with a different number of total entries J. The plot on the left shows this for the next *true* entry, regardless of being observed. As the total entries in the simulation J grows, the spacing from the first observed to the next true entry decreases. On average, there are 18.4 weeks from the first observed to the next true entry when $J = 50,000$. Decreasing the total entries to 8,000 in the simulation increases the average to 64 weeks.

The plot on the right in Figure C2 considers the spacing between the first observed entry in a catchment area and the next *observed* entry in that area. Once again, the distribution is shown for $J = 50,000$, $15,000$, and $8,000$. Note how in this case, there is no variation in the distribution across values of J. This is because, according to step 5 of the simulation

procedure, the probability of observing an entry is uniform across all entries, regardless of the catchment area or date.

Figure C3 shows the coefficient estimates from the estimating equation C1 for the event-study. The average coefficients over 100 iterations of the simulation are shown, as well as the 90% confidence interval. According to the DGP described in the procedure, the effect of each entry should be -0.1, regardless of entry order. Recall that this eliminates any bias from misclassifying entries as first entry when they are in reality some higher order entry.

Each plot corresponds to simulations with a different number of total entries J. For all three cases, the estimates are below the true effect of -0.1, leading to attenuation bias. The bias is larger as J grows. However, even in the overly exaggerated and infeasible case of 50,000 entries, the estimates are still about 50% of the true effect.

C.3 Different marginal effect of entries by entry order

Key assumptions:

1. $J = 8,000$, $T = 416$ and $C = 2,000$

2. The marginal effect of an entry now depends on its true entry order.

   This changes step 4 of the procedure. Specifically, now assume the following DGP:

$$y_{ct} = \begin{cases} w_{ct} - 0.1X_{ct} + r_{ct} & \text{if } X_{ct} \in \{0, 1\} \\ w_{ct} - 0.1 - 0.05(X_{ct} - 1) + r_{ct} & \text{if } X_{ct} \geq 2 \end{cases}$$

   where everything is defined as above, and $y_{ct} = 0$ is substituted whenever $y_{ct} < 0$.

   In this specification, the first true entry has a larger marginal effect than that of any subsequent entry (-0.1 versus -0.05).

3. The probability of observing an entry is as defined in step 5 of the procedure.

Results

Figure C4 shows the results of the event-study estimates for this procedure. As a reference, the plot on the left shows the case in which the marginal effect of entry is constant across true entry order (as specified in the previous section). Specifically, every entry leads to a permanent and immediate decrease of 0.1 of the outcome.

The plot on the right shows the estimation for the DGP defined above, where the effect of the first true entry is -0.1, and every subsequent entry has an effect of half that magnitude. Note that this simulation is introducing a bias from misclassifying higher order entries as first entries (that is, considering an entry in an area as the first because none of the previous entries in that area were observed).

The estimates show that the attenuation bias grows when the marginal effect of entry is decreasing with entry order. Importantly, this DGP still leads to estimates that are constant over weeks after entry. Furthermore, the simulations show that even under this scenario, the estimates are just attenuated towards zero, such that they provide a lower bound on the true effect.

C.4 Non-uniform probability of observing an entry

Key assumptions:

1. $J = 8,000$, $T = 416$ and $C = 2,000$
2. The DGP is as defined in step 4 of the procedure.
3. The probability of observing an entry depends on total entries.

   Originally, the probability of a simulated entry being observed was uniform across all entries. Now, assume that the probability of observing an entry depends on the total or maximum number of entries in a catchment area during the entire time period.

Specifically, let $N_c = \sum_{t=1}^{T} x_{ct}$ be the sum of all entries in an area c over this time period. Define N^{max} as the maximum of this variable. Then consider the following specifications for the probability that a simulated entry is observed:

$$\begin{aligned} \Pr(x_{ct} \text{ is observed}) &= (1/J)^{N_c^2} \\ \Pr(x_{ct} \text{ is observed}) &= (1/J)^{(N^{max}-N_c)^2} \end{aligned}$$

The first specification implies that it is more likely to observe entries in areas with more total entries. The second specification implies that it is less likely. Generally speaking, it seems that the first specification would be a more likely scenario than the second.

Results

Figure C5 shows the distribution of N_c, which is the total sum of entries in a catchment area (or maximum number of accumulated entries). The histogram shows that a large proportion of simulated areas have between 2 and 5 entries by the end of the entire time period considered.

Figure C6 shows the probability of observing at least one entry in a catchment area c relative to the total simulated entries in that area N_c. Three different specifications for the probability of observing an entry are shown. The circles correspond to the case where $\Pr(x_{ct} \text{ is observed}) = 1/J$, that is, where the probability of observing an entry is uniform across all entries. Naturally, this means that the probability of observing at least one entry in a catchment area c is increasing with the total simulated entries in that area N_c.

The triangles depict the case where $\Pr(x_{ct} \text{ is observed}) = (1/J)^{N_c^2}$, so that the probability sharply increases with total entries in an area N_c. Lastly, the squares show the opposite result, such that it is less likely to observe a first entry in catchment areas that had many entries.

Figure C7 shows the coefficient estimates from simulations with different specifications for the probability of observing a simulated entry. As a baseline, the first graph shows the estimates from before, with the probability of observing a simulated entry uniform across all simulated entries. The second plot shows the estimates when the probability of observing entries is increasing with the maximum or total entries in an area. The last plot corresponds to the opposite case.

The average estimates over 100 iterations of the simulation are shown, with the corresponding 90% confidence interval. Once again, in every specification, the estimates are below the true effect of -0.1, showing attenuation bias in the event-study results.

C.5 Probability of observing an entry dependent on entry's marginal effect

Key assumptions:

1. $J = 8,000$, $T = 416$ and $C = 2,000$

2. The DGP generates entries with large and small effects.

   For all entries J, randomly allocate half to entries with a large effect, and half to entries with a small effect. Each small entry has an effect of -0.1, while each large effect entry has an effect of twice that size. Specifically:

$$y_{ct} = \begin{cases} w_{ct} - 0.1X_{ct}^S - 0.2X_{ct}^L + r_{ct} & \text{if } w_{ct} - 0.1X_{ct} - 0.1\bar{X}_{ct} + r_{ct} > 0 \\ 0 & \text{otherwise} \end{cases}$$

   where X_{ct}^S are the accumulated small-effect entries, and X_{ct}^L are the accumulated large-effect entries.

3. The probability of observing an entry depends on the size of its marginal effect.

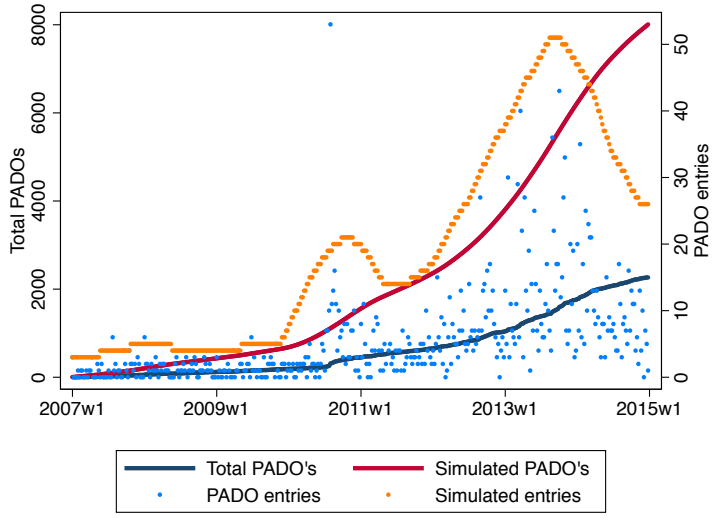
Define the probability of observing an entry differently for large vs small-effect entries. Specifically, let the probability of observing a large-effect entry be constant and four times larger than the constant probability of observing a small-effect entry. Then do the opposite so that small-effect entries are four times more likely to be observed.

Results

Note how the specification implies that the average effect in the true PADOs (the full 8,000) is -0.15, since there are equal numbers of large and small-effect PADOs. Due to the definition of the probabilities of observing an entry, in the first simulation, 80% of observed entries are large-effect entries, while in the second only 20% are large.

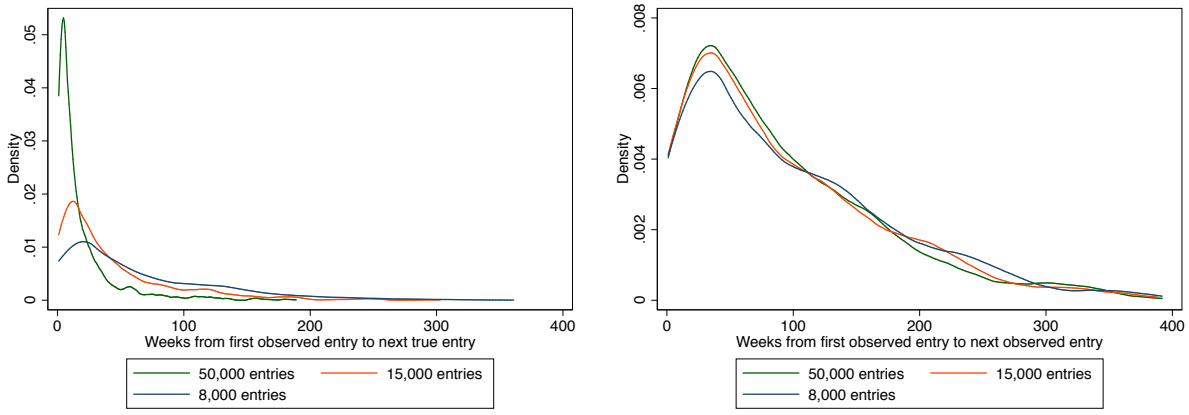
Figure C8 shows the coefficient estimates. If the probability of observing small-effect entries is larger, then there is a clear attenuation bias, such that the estimates are closer to the effect of -0.1 corresponding to small-effect entries. However, when the large-effect entries are more likely to be observed, the estimates do not exceed the average effect of -0.15, such that there is no over-estimation of the true effect.

Figure C1:
Evolution of COFEPRIS data entries and simulated entries over time



Notes: This graph plots the distribution of entries over time for the COFEPRIS data, as well as for a simulation of 8,000 entries.

Figure C2:
Distribution of spacing from observed first entry to next true or observed entry in simulated data

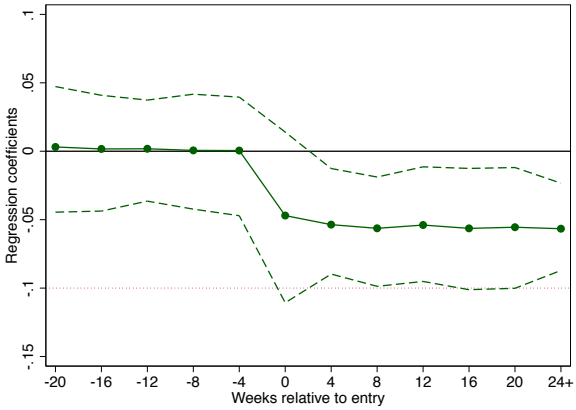


(a) To next true entry

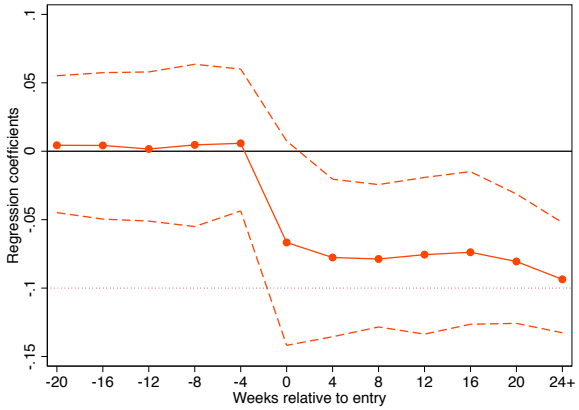
(b) To next observed entry

Notes: These plots show the distribution of the spacing from the observed first entry in a simulation to the next entry. The plot on the left considers the next *true* entry, regardless of being observed. The graph on the right considers the next *observed* entry. The distribution is shown for three different simulations, each with a different number of total entries J.

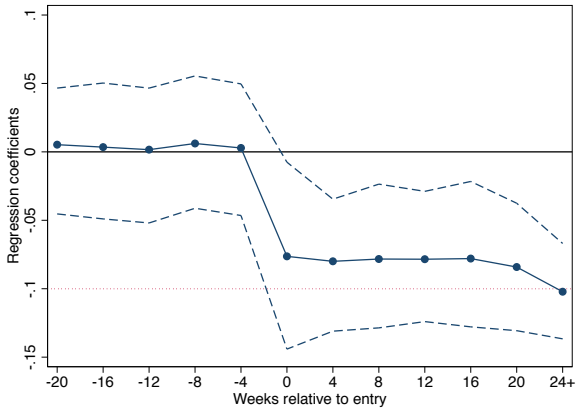
Figure C3:
Estimates for the simulated data: Variations in total entries



(a) 50,000 total entries



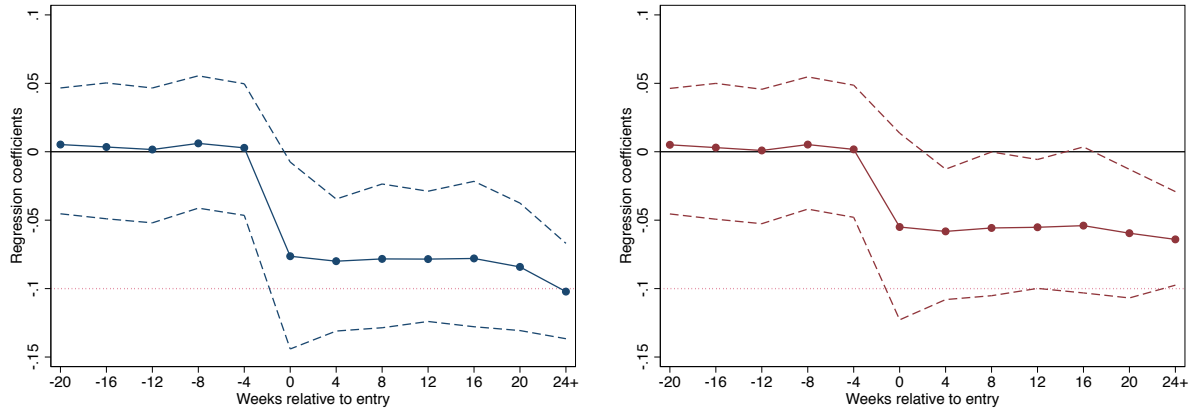
(b) 15,000 total entries



(c) 8,000 simulated entries

Notes: These plots show the coefficient estimates from equation C1. The average coefficient over 100 simulations is shown, with the corresponding 90% confidence interval. Each plot corresponds to a different number of total simulated entries. Based on the DGP, the effect of each entry, regardless of entry order, should be -0.1, which is referenced with a dotted line.

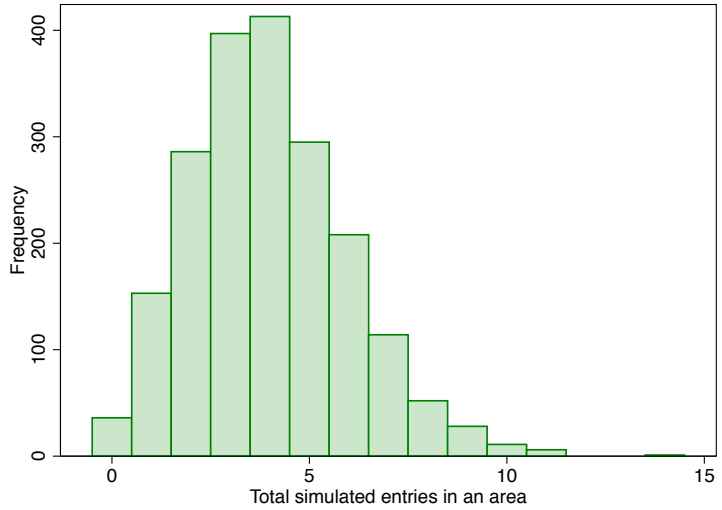
Figure C4:
Estimates for the simulated data: Variations in marginal effect of entry by true entry order



(a) Constant marginal effect of entry (b) Marginal effect decreasing with entry order

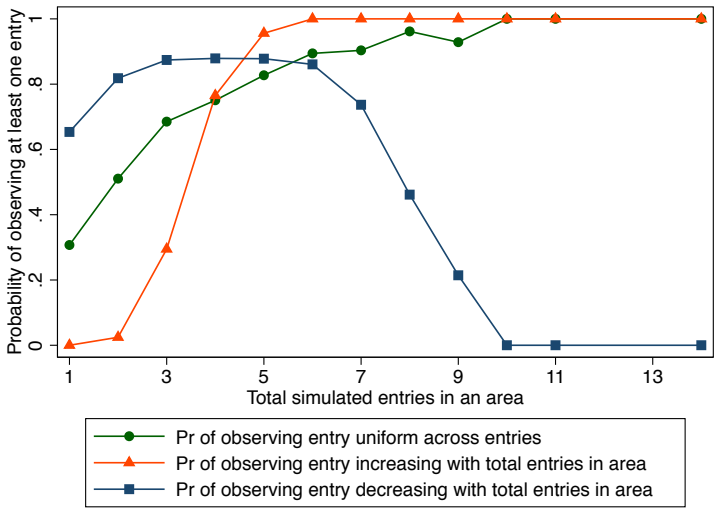
Notes: These plots show the coefficient estimates from equation C1. The average coefficient over 100 simulations is shown, with the corresponding 90% confidence interval. The total simulated entries are set to 8,000. The plot on the left assumes that the DGP is such that every entry, regardless of entry order, has a constant effect of -0.1 on the outcome. The graph on the right corresponds to simulations where the effect of the first true entry on the outcome is -0.1, while the marginal effect of subsequent entries is just -0.05. Based on the DGP in both cases, the effect of the true first entry should be -0.1, which is referenced with a dotted line.

Figure C5:
Distribution of total sum of entries in a catchment area



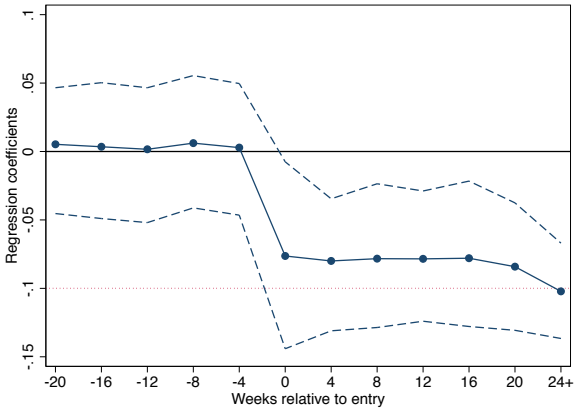
Notes: This graph shows a histogram depicting the frequency of the total or maximum number of entries in a catchment area during the entire time period. The total entries in this simulation is 8,000.

Figure C6:
Probability of observing at least one entry in an area as a function of total entries in an area

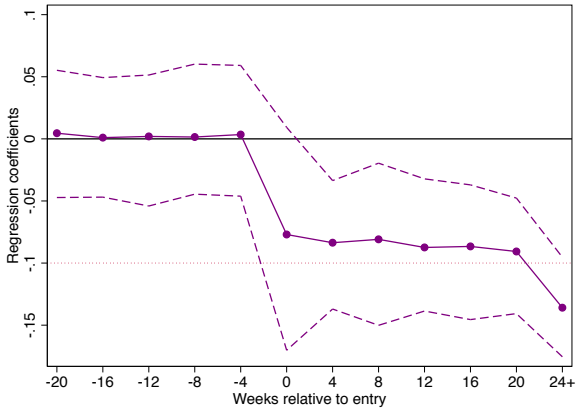


Notes: This graph shows the probability of observing at least one entry in a catchment area as a function of the total simulated entries in that area. Each line corresponds to a different specification of the probability that a simulated entry is observed. The total entries in these simulations is 8,000.

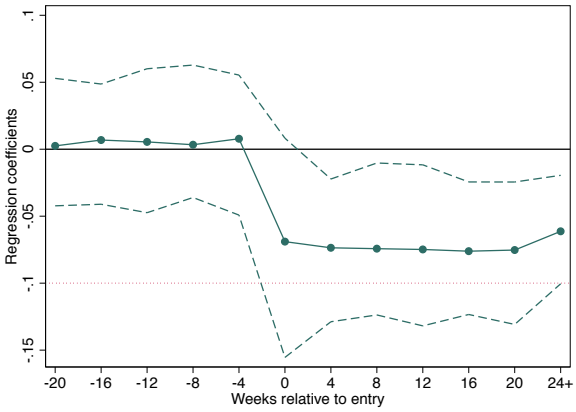
Figure C7:
Estimates for the simulated data: Variations in probability of observing an entry



(a) Uniform probability



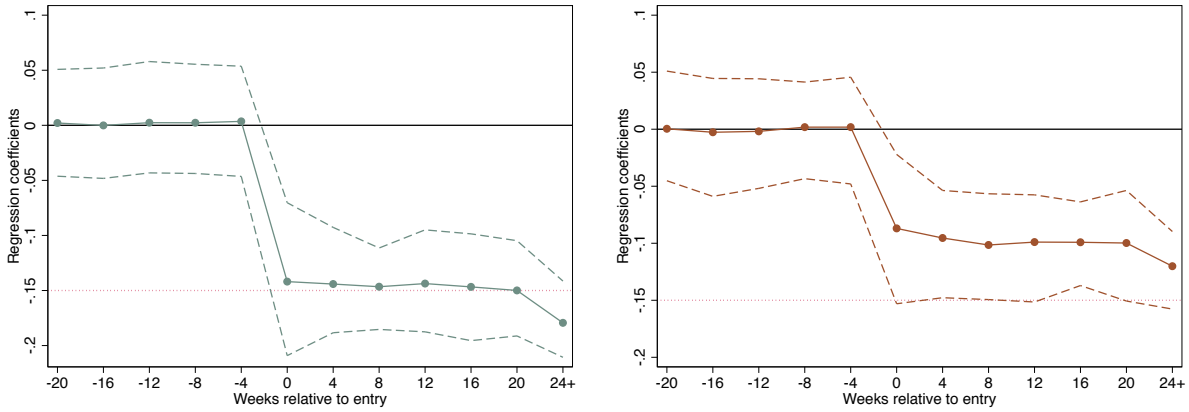
(b) Increasing with total entries in area



(c) Decreasing with total entries in area

Notes: These plots show the coefficient estimates from equation C1. The average coefficient over 100 simulations is shown, with the corresponding 90% confidence interval. Each plot corresponds to a different specification for the probability of observing a simulated entry. Based on the DGP, the effect of each entry, regardless of entry order, is -0.1, which is referenced with a dotted line.

Figure C8:
Estimates for the simulated data: Probability of observing an entry dependent on entry's marginal effect



(a) Large-effect entries more likely observed (b) Small-effect entries more likely observed

Notes: These plots show the coefficient estimates from equation C1. The average coefficient over 100 simulations is shown, with the corresponding 90% confidence interval. Each plot corresponds to a different specification for the probability of observing a simulated entry as it relates to the marginal effect of an entry. Based on the DGP, the effect of each entry, is -0.1 for small-effect entries, and -0.2 for large ones. The composition in the true entries is 50-50, so that the average effect is -0.15, which is referenced with a dotted line.

D PADO Entry in Public Clinic Catchment Areas

Figure D1 presents the cumulative number of PADOs and the number of entrants per week for the full COFEPRIS dataset. The same pattern as in Figure 1 in the main text holds. Note that there are very few entires prior to 2007.

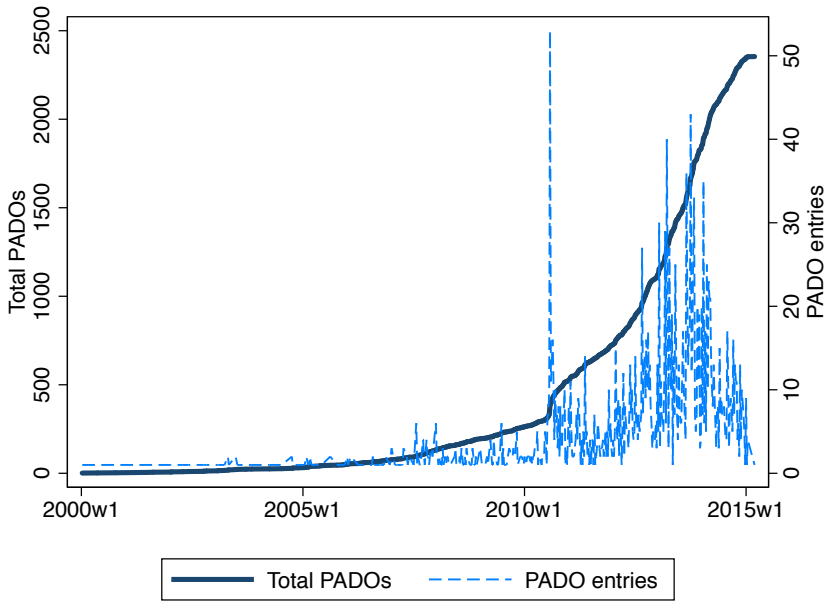
Figure D2 shows a map with the location of all PADOs in the COFEPRIS dataset. The map also shows population density at the municipality level. Note how more dense areas are those that tend to have more PADOs.

Figure D3 shows four examples of PADO entry within a catchment area. These clinics were randomly chosen, and the caption identifies the institution and state for each. The left axis measures the total number of PADOs within the catchment area in each week from 2007 to 2014. The right axis indicates the number of PADO entrants in each week (evidently, this number is zero for most all weeks).

Figure D3b shows the clearest example. In this particular catchment area, I do not observe any PADOs until the first entrant in early 2013. This results in the first jump observed in the graph. Afterwards, the next entry only occurs until late 2014.

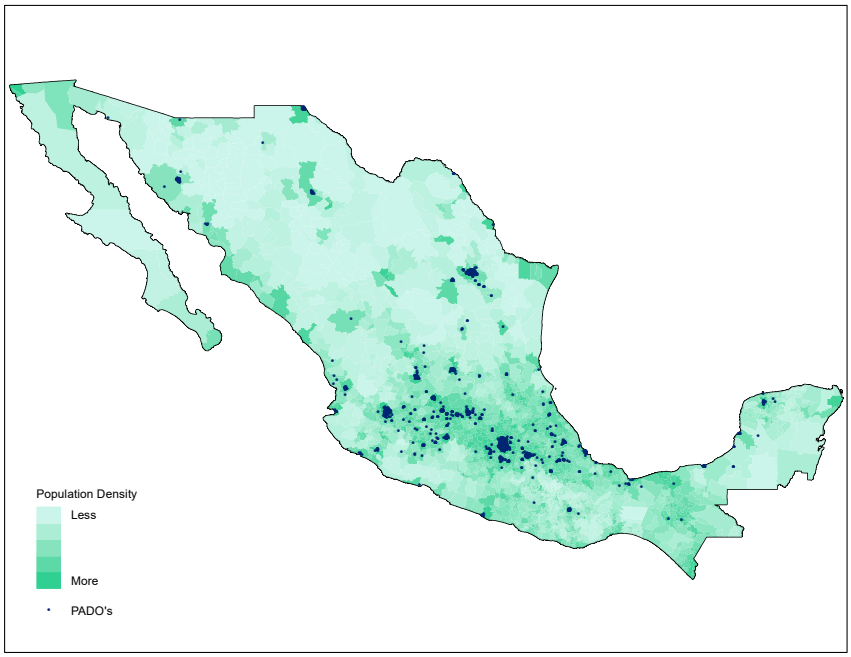
Note that, because the PADO data goes further back than 2007, it is possible that the total number of PADOs in a catchment area is larger than zero in the first week of 2007. This is the case in Figures D3a and D3d, where there were two and four PADOs at the beginning of the 2007-2014 time frame, respectively. On these graphs, the existing number of PADOs before 2007 are all recorded as having entered in the first week of 2007, simply as a way of showing on the graph the actual number of PADOs at the beginning of this time frame. The main results hold when these clinics are excluded. Also note that there are cases in which entry is not limited to a single PADO entrant. This is evident in Figures D3a and D3c.

Figure D1:
PADO Entry and Accumulated PADOs



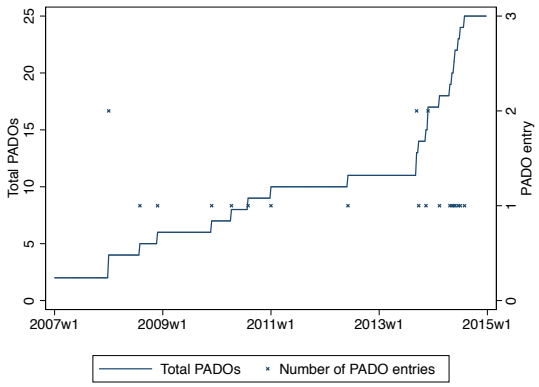
Notes: This graph plots the country-level PADO entries observed in the COFEPRIS dataset on a weekly basis, as well as the cumulative count of PADOs.

Figure D2:
Location of PADOs

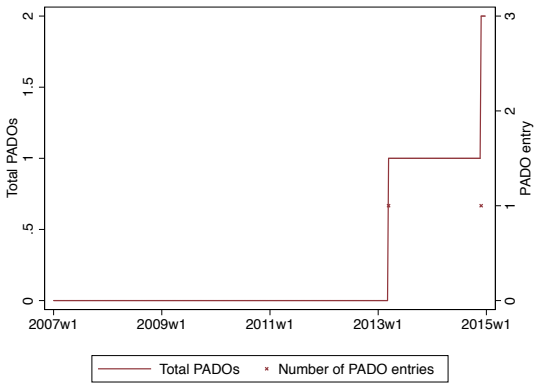


Notes: This map shows the geographic distribution of the PADOs observed in the COFEPRIS dataset. It also shows population density at the municipality level.

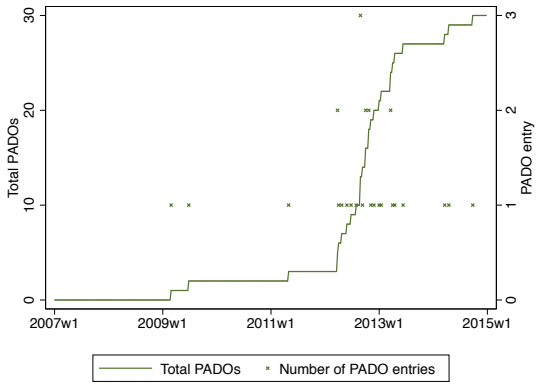
Figure D3: PADO Entry in Outpatient Clinic Catchment Areas



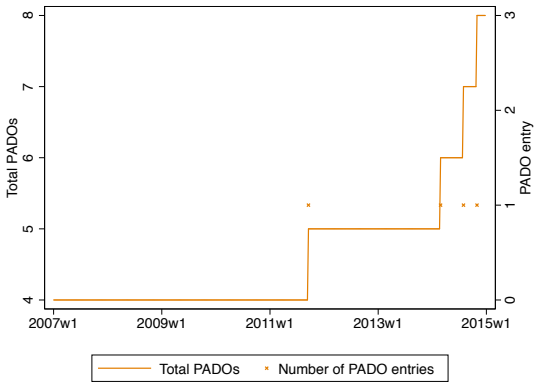
(a) An SSA clinic in DF



(b) An SSA clinic in the state of Mexico



(c) An SSA clinic in Jalisco



(d) An IMSS clinic in Queretaro

Notes: These plots provide four random examples of PADO entry in a public outpatient clinic catchment area, as defined by a 5 kilometer radius. Each graph indicates entry weeks as well as the number of entrants. The plots also provide the total PADO count within the catchment area. The time frame here is limited to the years of analysis (2007 to 2014).

E Classification of Acute Respiratory Infections

All diagnoses in the Reported Cases Dataset and the Admissions Data for SSA Hospitals are classified using ICD-10 codes. Additionally, SSA uses a specific definition of what constitutes ARIs. Table E1 lists the codes for ARIs.

Table E1:
Classification of Acute Respiratory Infections

Bacterial ARIs	
A15	Respiratory tuberculosis (bacteriologically and histologically confirmed)
J13-J15	Pneumonia due to bacteria
Viral ARIs	
J00	Acute nasopharyngitis (common cold due mostly to the rhinovirus and other viruses)
J12	Viral pneumonia
Other or unspecified ARIs	
A16	Respiratory tuberculosis (not bacteriologically and histologically confirmed)
H65.0-H65.1	Acute serous otitis media, other acute nonsuppurative otitis media
J01-J06	Acute upper respiratory infections (sinusitis, pharyngitis, tonsillitis, laryngitis, tracheitis, epiglottitis, croup) except nasopharyngitis
J16-J18 except J18.2	Other pneumonias except hypostatic
J20-J21	Bronchitis and bronchiolitis

Notes: Based on information from SSA.

F More Details on Outpatient Clinics Sample

As detailed in Section 4, I identify outpatient clinics that register PADO entry within a 5 kilometer catchment area. This leaves me with effectively 2,606 clinics. However, in order to guarantee at least a full year pre and post-entry, I exclude 346 clinics where the first entry occurred in either 2007 or 2014.

Table F1 shows some summary statistics for these excluded clinics and compares them to the 2,260 clinics in my sample. The excluded clinics register significantly more diagnoses and are less equipped in terms of consulting rooms and medical staffing, although they do not differ significantly in terms of their institution composition.

Table F1:
Descriptive Statistics: Clinics in sample vs excluded clinics

	Clinics in sample	Excluded clinics
All new diagnoses per 100,000	54.20	69.06**
	(127.09)	(150.30)
ARI diagnoses per 100,000	34.75	45.47**
	(86.82)	(107.43)
Fraction IMSS	0.16	0.13*
	(0.37)	(0.33)
Fraction SSA	0.68	0.71
	(0.47)	(0.45)
Fraction IMSS-Oportunidades	0.07	0.08
	(0.26)	(0.28)
Fraction ISSSTE	0.06	0.05
	(0.23)	(0.22)
Fraction other local government	0.03	0.03
	(0.16)	(0.16)
Total exam rooms, 2014	6.85	4.52***
	(9.52)	(6.86)
Total doctors, 2014	12.67	8.14***
	(21.60)	(15.28)
Total public outpatient clinics	2,260	346
Observations	940,160	143,936

Notes: This table shows summary statistics for clinics in the sample and clinics that were excluded. Excluded clinics are those that have their first PADO entry either in 2007 or 2014. Means shown for each variable, with standard deviations in parentheses. Significance of difference in means test shown.
*** p<0.01, ** p<0.05, * p<0.1