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

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Abstract

In settings with inefficient public provision, innovations in private-market healthcare delivery may be welfare-improving by increasing access, but may be sacrificing on quality. I study the expansion of retail clinics at private pharmacies in Mexico. I find that entry leads to large declines in public-sector emergency room visits and a small but significant reduction in public clinic visits for relatively mild respiratory infections. I also find a significant increase in public clinic visits for chronic conditions and a slight decline in emergency room visits, consistent with better disease management. However, I estimate a strong association between retail clinics and a shift toward stronger antibiotics in private-market sales. Hence, although retail clinics improve access to healthcare, they may be overselling their patients.

JEL codes: I11, I18, I15
Keywords: primary care; retail clinics; provider choice; quality of care; prescribing behavior

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1 Introduction

Congestion and inefficiencies in public service provision are common across settings (e.g., education, security, waste disposal).[1] This public provision often coexists with private market alternatives, some of which focus on offering low-cost solutions. Primary healthcare delivery is one such instance where private and public markets coexist in many countries.

Public provision of healthcare has been shown to be inefficient in many developing country settings (Das et al., 2016; Dizon-Ross et al., 2017). Among other issues, congestion at facilities may decrease access (Dupas and Miguel, 2017; Ashraf et al., 2014; Christensen et al., 2021).[2] Although private health services may be less congested, they are expensive, usually paid for out-of-pocket, and may not offer higher quality (Leive and Xu, 2008; Das and Hammer, 2014). Market innovations in healthcare delivery, usually in the form of low-cost, limited-service private providers – for example, retail clinics and mobile clinics – offer services that are cheaper than traditional private doctors and quicker than public clinics.[3] However, characterizing the interplay between these public and private providers is essential for understanding these healthcare markets and informing policy design.

This paper analyzes how entry of a low-cost private provider affects public healthcare provision and explores one potential channel on which quality of care may be lower at these new providers. Specifically, I focus on the expansion of private pharmacy-adjacent doctors' offices (PADOs) – essentially, retail clinics at private pharmacies – in Mexico.[4] This setting

[1]See, for example, Mbiti, 2016; Alderman et al., 2001; Urquiola, 2016 for education; Bayer and Pozen, 2005; Mukherjee, 2015; Mumford et al., 2016 for the prison system; and Bel et al., 2010; Zafra-Gómez et al., 2016 for solid waste management.

[2]Congestion is also related to high patient-worker ratios, which, among others, may be due to low staffing and absenteeism (Banerjee and Duflo, 2006).

[3]Other innovations include 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., 2019; Goldberg et al., 2018). These alternatives are often cost-effective, especially when exploiting existing private networks, such as retail-sector drug stores (Cohen et al., 2015). 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).

[4]These PADOs are not *exactly* identical to retail clinics (low-cost, walk-in clinics staffed by nurse practitioners) in the US and other developed countries. However, retail clinics at US pharmacies – such as CVS

allows me to explore potential trade-offs between access and quality in healthcare, which may be informative of other developing world contexts.

The analysis exploits data from the registry of PADOs from the Ministry of Health (SSA). The data include 6,360 PADOs by the end of 2019, although I restrict my attention to 5,111 PADO entries from 2005 to 2015 due to the availability of healthcare utilization data.

Using anonymized patient records from a medium-sized PADO chain as a case study, I begin by documenting that over half of all PADO visits at this chain are for acute respiratory infections (ARIs). Thus, I focus the initial analysis on the effect of PADOs on public healthcare utilization for ARIs.

I obtain data on the three main types of public healthcare facilities: outpatient clinics, emergency rooms (ERs), and hospitals. These data allow me to construct a balanced panel recording ARI visits or hospital admissions at each facility during four-week periods. Using geographic coordinates of facilities and PADOs, I match each PADO to all facilities within a 5 km radius. I then aggregate visits and hospitalizations as a measure of public healthcare utilization in the local healthcare market surrounding each PADO. As a robustness check, I also consider a 2.5 km radius and generate inverse-distance weighted aggregates.

I identify the effect of PADO entry on utilization using an event study design with time period and PADO fixed effects (FE). The main identifying assumption is that, absent PADO entry, utilization trends would have been similar across locations. I partially test this by inspecting the pre-entry coefficients. Considering the growing literature on the pitfalls of staggered timing difference-in-differences (DiD), I also validate the research design by showing the De Chaisemartin and d'Haultfoeuille (2020) estimator that is robust to heterogeneous average treatment effects (ATE) in the online appendix.

I estimate a significant decline in public clinic visits for ARIs of 2-3% after PADO entry, which translates into an average of 21-33 fewer visits per week. This finding is robust to various specifications. For ER visits, I find a large decrease of 50% for ARI visits, or about

Minute Clinics – are conceptually similar. Therefore, I somewhat abuse terminology and refer to PADOs as retail clinics.

12 less per week.[5] Lastly, I find weaker evidence of a 12% decline in ARI hospital admissions. Across specifications, coefficients on the leads of entry are all close to zero, helping validate the empirical design. Results using the estimator in De Chaisemartin and d'Haultfoeuille (2020) hold for outpatient clinics and ERs, but are less robust for hospitalizations, suggesting there may be no significant effects at hospitals. Overall, these estimates show that PADOs are pulling ARI patients away from public providers at the outpatient level.

Supplementary analyses using additional survey and administrative data are shown in the online appendix. First, PADOs are associated with a decline in waiting times and perhaps an increase in the time doctors spend with patients at public clinics. This is consistent with PADOs leading to decongestion of these busy facilities. However, the evidence does not suggest significant increases in the probability of seeking medical attention when sick. From the physician supply side, I do not find significant associations between PADOs and doctors, although point estimates suggest an increase in total doctors (public and private) and perhaps a small decline in public doctors. Additional administrative data suggest that this decline in staffing at public facilities is economically insignificant.

To better understand the public healthcare market and informed by the case study, I then present event study estimates of utilization for other large diagnostic groups. As a subset of ARIs and due to being a more serious infection, pneumonia acts as a proxy for severe ARIs. I find no effects on pneumonia visits at public clinics, although there is a significant impact of around 26% fewer ER visits. For gastrointestinal diseases (GIDs), I again find no effects on clinic visits but a strong significant decline at ERs. Lastly, I estimate a significant increase in clinic visits for chronic conditions, coupled with weak evidence of a decline in ER visits, which may be due to better management of these diseases and is consistent with decongestion effects at the crowded public clinics.

Altogether, the estimates on utilization suggest that PADOs are pulling patients away from ERs for multiple infectious diseases and from outpatient clinics for relatively mild ARIs,

[5] Similar substitution patterns between retails clinics and ERs have been documented in the US (Alexander et al., 2019; Sussman et al., 2013; Ashwood et al., 2016).

which allows more patients with chronic conditions to visit the public clinics. These results seem to suggest that PADOs are welfare-improving for access, particularly by decongesting busy facilities and allowing for more chronic disease visits. However, due to the vertical integration with private pharmacies, there may be additional costs to consider.

Given the focus on ARIs, one particular cost may be related to changes in antibiotic prescriptions. Going back to my case study, I document that doctors at this PADO chain prescribe antibiotics for over 60% of ARI visits, even after accounting for differences across physicians and over time. I then show that this rate is high even for patients diagnosed with the common cold, which is most often caused by a virus. Lastly, I report that strong antibiotics are more likely to be prescribed than milder types, conditional on an ARI diagnosis and an antibiotic prescription. These facts motivate the exploration of the relationship between PADO expansion and antibiotic sales at private pharmacies.

I obtain proprietary data from a pharmaceutical consulting company that allows me to observe sales at private pharmacies by penicillin product at the city level on a monthly basis from 2010 to 2012. I map cities to municipalities and construct a balanced panel of 183 products across 563 municipalities. I classify products into narrow spectrum and broad spectrum penicillin by matching publicly available data. Broad spectrum penicillin is stronger, more expensive, and medical guidelines caution against overusing this antibiotic as a first course of action due to the low probability of being medically necessary for common infections and due to the risk of fostering bacterial resistance (Leung et al., 2011).

I explore the association between PADOs and sales of narrow and broad spectrum penicillin under a continuous treatment DiD (i.e., PADOs per 10,000 interacted with an indicator for narrow or broad spectrum penicillin), with time period, municipality, and product FE. Additional specifications include more restrictive FE and controls. Due to the pitfalls of staggered timing DiD with a continuous treatment that have been recently documented (Callaway et al., 2021), I caution against making a strong causal interpretation. However, I also present an instrumental variables (IV) approach – using the share of pharmacies in a municipality in 2009 that are retail chains that also sell non-pharmaceutical products – that may provide some support for a causal claim.

Estimates show that PADO expansion is associated with a shift away from narrow spectrum penicillin toward stronger types. In the base specification, an additional PADO per 10,000 people is associated with a 12% decline in narrow spectrum types and a 17% increase in broad spectrum types.[6] I find no evidence of an increase in the total amount. Based on the previous results that PADOs are probably not seeing more serious ARI cases, and to the extent that stronger penicillin is likely to be medically unnecessary and more expensive, I interpret this result as suggestive evidence that PADOs may sacrifice quality of care due to their ties to the private pharmacies. However, data limitations – such as not being able to directly link sales with PADO doctor prescriptions – invite further research in this area.

Overall, this study shows that PADOs may be improving access to healthcare by shuffling patients away from congested public ERs, and away from public clinics for milder ARIs, allowing an increase in visits for chronic conditions. However, there may be additional costs, such as a shift in prescriptions toward stronger antibiotics. Calculating the net effect on welfare is beyond the scope of this paper, although the findings do emphasize a trade-off between access and quality. Results suggest that better regulation of PADOs and possibly strategic partnerships between PADOs and the public sector may be welfare improving.

This paper contributes primarily to the literature exploring healthcare delivery alternatives in developing countries, such as community workers (Björkman Nyqvist et al., 2019; Wagner et al., 2020) and informal providers (Sudhinaraset et al., 2013). However, while most studies focus on health outcomes, I analyze substitution away from public facilities. Given that public and private providers coexist and considering the vertical integration of PADOs with pharmacies, I am able to explore the trade-off between an increase in access to care and potentially negative effects on the quality of care offered at the retail clinics.

[6] The data do not allow me to explore potential mechanisms. However, this result speaks directly to the literature characterizing prescription practices in multiple contexts, including induced demand (Currie et al., 2011; McGuire, 2000; Iizuka, 2007; Gottschalk et al., 2020), effects of increased competition (Bennett et al., 2015; Bennett and Yin, 2016) and prescription differences by type of provider (Das et al., 2016).

2 Context

Healthcare in Mexico. Public and private providers coexist within the Mexican healthcare system. According to the 2012 National Health Survey (ENSANUT), 73% of the population was covered by the public system. Publicly provided healthcare is composed of disjoint institutions targeting different populations. The two main subsystems are the Mexican Social Security Institute (IMSS) for formal sector workers, and the Social Protection System in Health (commonly referred to as Seguro Popular) for informal workers and the unemployed. Each institution has its own network of public providers, with the Ministry of Health (SSA) directly in charge of the Seguro Popular subsystem.[7] The public system does not cover healthcare costs at private providers, and due to low private insurance rates,[8] most utilization at private facilites is paid out-of-pocket.[9]

Public healthcare in Mexico is not universal in practice, lacks infrastructure, and has important supply shortages and long waiting times (OECD, 2016). Private health services on the other hand are costly. 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 during their last sickness spell, conditional on seeking care (see Tables A1 and A2 in the online appendix).[10]

Pharmacy-adjacent doctors' offices. Perhaps due to inefficiencies in the public system, private healthcare is a growing market in Mexico. One private-market alternative has been PADOs. Conceptually similar to retail clinics in other contexts, PADOs consist of a doctor's office located within a private pharmacy, offering outpatient consultations on a first-come, first-served basis. PADOs are vertically integrated with the private pharmacies and doctors

[7] The public system covers 30% of the population at IMSS, and 38% at SSA. Smaller subsystems cover the remaining 5% (ENSANUT 2012).

[8] Less than 1% of the population is privately insured (ENSANUT 2012). Private insurance is primarily employment-based at higher wage levels and usually only covers catastrophic events like hospitalizations.

[9] According to the WHO's NHA indicators for 2014, out-of-pocket as a share of total health expenditures was 44% in Mexico, well above the 33% average for Latin American countries.

[10] Around 30% of public system affiliates seek private primary care when sick (ENSANUT 2012).

receive a salary from the pharmacy itself, including bonuses.[11] Services provided focus mostly on acute infections (Díaz-Portillo et al., 2015).

PADOs operate during usual pharmacy business hours (including Saturdays and Sundays at many locations), and waiting times are 21 minutes on average, or roughly a quarter of the waiting times in the public sector (ENSANUT 2012). Consultations cost on average 39 pesos (3 USD),[12] and many are free, while traditional private providers charge almost seven times as much at 269 pesos on average (see Table A3 in the online appendix).[13]

PADOs first appeared in 1997 at a chain pharmacy and have gradually expanded over time as more chains roll out their own PADOs and non-chain pharmacies also enter this market space.[14] Some of this expansion coincides with a regulation enacted in August 2010 that prohibited over-the-counter sales of antibiotics.[15] While this may suggest that PADO growth was a response to this policy – as argued in Pérez-Cuevas et al. (2014) – expansion had already been occurring during the 13 years prior.

Regulations are very lax. To open a PADO, a pharmacy must obtain a notice of operations from the Federal Commission for the Protection against Sanitary Risks (COFEPRIS), although no regulatory approval is necessary. Infrastructure and equipment requirements are also quite lenient. Hence, many pharmacies simply adapted part of their storage or shelf space in order to open their own PADO (FUNSALUD, 2014).

[11]Wages in Mexico are very low and there is vast inequality. In 2015, monthly base salaries at PADOs were on average 5,500 pesos (435 USD), although monthly income (including additional payments and bonuses) was 8,500 pesos (672 USD). This difference represents financial incentives based on patient volume, prescriptions, or other performance metrics. See Díaz-Portillo et al. (2015) for more information.

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

[13]According to the 2012 income and expenditures survey (ENIGH), PADO prices represent 6% of the average daily household income and traditional private providers 43%.

[14]Expansion through large chains has been observed in other settings, such as the rise of retail clinics in the US from small operators to large, concentrated corporations (Laws and Scott, 2008).

[15]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, respectively.

2.1 PADO Entry Data

When PADOs (or any other provider) obtain a notice of operations, SSA assigns a unique identifier with basic information. I obtain the full roster of PADOs up to 2019 from SSA.[16] The data include the geographic coordinates of each PADO and their opening date for a total of 6,360 PADOs by the end of 2019. Figure 1 shows PADO entries and total cumulative PADOs over time, zooming in to the study period from 2005 to 2015. The data show a tenfold increase, from 598 PADOs at the beginning of 2005 to 5,714 by the end of 2015.[17]

Potentially missing PADOs in the roster. Given the lax regulations and state-capacity challenges in Mexico, it is possible that this roster is incomplete.[18] However, other studies have also used this roster (see, for example, Colchero et al. 2020) and it is unlikely that undercounting would be a big problem since the majority of PADOs are located in urban areas at large pharmacy chains that would probably not circumvent the registration requirement. Nevertheless, I discuss the potential implications for the empirical strategy below.

2.2 Case Study: A Medium-Sized PADO Chain

Understanding which services are used at PADOs is a crucial first step for estimating their effect on public healthcare utilization. Although is well-documented that PADOs offer limited services (Díaz-Portillo et al., 2015; Colchero et al., 2020), I motivate my analysis with descriptives from a PADO chain that was willing to share its patient information.

[16] Data are available at `http://www.dgis.salud.gob.mx/contenidos/intercambio/clues_gobmx.html`, last accessed July 21, 2021.

[17] Online appendix Figure A1 shows the distribution of entries from 1997 to 2019 as well as the within-year distribution, while Figure A2 presents a series of maps with the location of new PADOs over time.

[18] A report commissioned by COFEPRIS and prepared by a private consulting company reports 15,000 PADOs in existence in 2014 (see FUNSALUD 2014). This would amount to 10,000 missing PADOs in the roster, which is unlikely. It is more likely that this is a miscalculation of the consulting company. According to a freedom of information request (number 1215100141817), COFEPRIS no longer has this document.

Data. I procured all (anonymized) patient records from a medium-sized PADO chain from September 2013 to August 2015.[19] This chain had around 120 locations across many states in 2015. For each patient visit, I observe the date on which it occurred, a unique identifier for the doctor that provided the consultation, the diagnosis made by the doctor, and all medications prescribed. I drop patient visits that are associated with more than one diagnosis (8.8% of the data). This results in a total of 355,444 single-diagnosis visits.

Main diagnoses. I classify diagnoses into 15 main categories and a catch-all group for the remaining ones. Since this PADO does not use ICD-10 codes, I categorize diagnoses by searching and sorting the most common strings in the data. The top left graph in Figure 2 shows the distribution of diagnoses. ARIs make up the bulk of visits with 55% of the total. The second most common diagnosis, corresponding to GIDs, only accounts for about a quarter of this at 14%. Although this is a single PADO chain, these results line up well with survey data (appendix Table A3) and motivate the initial focus on ARIs.

3 Effects on Public Healthcare Utilization for ARIs

3.1 Data

Outpatient clinics. I obtain data on utilization at public outpatient clinics directly from SSA's offices. These data are available from 2005 to 2015, effectively restricting the analysis to this period. 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.[20] I identify ARIs based on ICD-10 codes (see online appendix Table A4 for a list of diagnoses). These data also contain information on pneumonia (available only from 2007 to 2014), GIDs, chronic conditions, and all visits, which will be

[19] The data-sharing agreement does not allow me to disclose any identifying information from this firm.

[20] These data are available at http://www.dgis.salud.gob.mx/contenidos/basesdedatos/bdc_recursos_gobmx.html, last accessed July 21, 2021.

analyzed in Section 4. The data include information on 16,936 outpatient clinics from the four main public subsystems: SSA, IMSS, ISSSTE, and IMSS-OP.[21] I aggregate the data into four-week periods.

Emergency rooms. Data on all ER visits in the SSA subsystem are publicly available from 2008 to 2015.[22] Unfortunately, information is not available for other institutions. The visit-level data include the date, diagnosis (using ICD-10 codes), and ER facility identifier. I again obtain geographic coordinates and generate counts by diagnosis at the facility-by-four-week-period level. I eliminate ERs that have zero visits over more than half the observed periods, resulting in 622 ERs recording about 67.5 million visits during these years.

Hospitals. Data on all hospital admissions in the SSA subsystem are publicly available for the 2005-2015 period.[23] There is no similar information for other public hospitals. The data include the date for each admission, diagnosis (using ICD-10 codes), and hospital identifier. I again obtain geographic coordinates and generate counts by diagnosis at the hospital-by-four-week-period level. I eliminate hospitals with zero admissions over more than half the observed periods. The data then consist of 676 hospitals recording about 26.9 million hospitalizations. Since ERs are generally located at hospitals, 573 of these hospitals correspond to an ER in the previous dataset.

3.2 Empirical Strategy

The general idea is to construct a measure of public healthcare utilization in the surrounding area of each PADO and estimate an event study regression that measures changes in utilization around entry. I describe each step below.

[21] ISSSTE is the Institute for Social Security and Services for State Workers and IMSS-OP (IMSS-Oportunidades) is a separate branch of IMSS. A total of 11,575 clinics (69% of the total) belong to the SSA subsystem, 3,757 (22%) to IMSS-OP, 1,082 (6%) to IMSS, and 522 (3%) to ISSSTE.

[22] These data are available at http://www.dgis.salud.gob.mx/contenidos/basesdedatos/bdc_urgencias_gobmx.html, last accessed July 21, 2021.

[23] These data are available at http://www.dgis.salud.gob.mx/contenidos/basesdedatos/bdc_egresoshosp_gobmx.html, last accessed July 21, 2021.

Matching healthcare facilities to PADOs. For each of the 5,116 PADO entries occurring between 2005 and 2015, I identify all healthcare facilities within a 5 km radius of the PADO. Given the available years for the ER data, I only consider 4,488 PADO entries in this case. Some public healthcare units may be matched with more than one PADO event, and some PADOs may not be matched to any facilities. I then aggregate clinic and ER visits and hospital admissions from the matched facilities for each PADO. This effectively constructs a measure of utilization in the surrounding area of the PADO, which I essentially consider to be a local healthcare market.

As robustness checks, I also restrict to facilities that are within 2.5 km of the PADO, generate inverse-distance weighted aggregates, and include PADO events that occur either before 2005 or after 2015. I also obtain the number of matched facilities to use as weights. Lastly, I identify the entry rank for each matched facility in each PADO entry event.[24] I generate the average of the entry rank of all matched facilities for each PADO event as an indirect measure of the relative novelty of a PADO in each location.

Descriptive statistics. Table 1 shows summary statistics of healthcare utilization from the matched PADO events. I show the number of matched facilities, the average entry rank for those facilities, and the average distance to the PADO. I then present the actual utilization variables at the PADO-by-four-week-period level.

Panel A (outpatient clinics) shows descriptives for 5,111 PADO events. A large fraction of the matched clinics correspond to SSA facilities, and on average there are 14 matched clinics per PADO. This is expected since there is a much larger number of clinics than hospitals and because these data include the four largest public subsystems, which often overlap geographically.

Panel B presents statistics for 157 PADO events matched to SSA ERs. All matches are one-to-one. The smaller number of events is driven by the reduced number of available data

[24] If a clinic is matched with both PADOs a and b, and the entry date of a is before b, then this clinic has an entry rank of one in its match with a and two in its match with b.

years and by the fact that there is a much smaller number of ERs than clinics. Lastly, panel C shows 444 PADO entries matched to SSA hospitals. Almost all matches are again one-to-one, which is expected given the overlap between the ER and hospital data.

As for utilization, ARIs make up a large share of visits and hospital admissions. From the diagnoses considered, GIDs are the second most prevalent for clinic and ER visits. As expected, pneumonia (as a share of ARIs) is larger for hospitalizations, and chronic conditions are more prominent in hospital admissions than in outpatient and ER visits.

Empirical strategy. I estimate event study regressions of the following form:

$$\sinh^{-1}(y_{pt}) = \sum_{\tau=-A}^{A} \beta_\tau \mathbb{1}_{[t-E_p=\tau]} + \gamma_t + \theta_p + \varepsilon_{pt} \tag{1}$$

where y_{pt} is public healthcare utilization in the surrounding area of PADO p during the four-week time period t, $\sinh^{-1}$ is the inverse hyperbolic sine function, $\mathbb{1}_{[\cdot]}$ is the indicator function, E_p is the period in which PADO p enters the market, $A > 0$ defines the number of leads and lags, γ_t are time period FE, θ_p are PADO event FE, and ε_{pt} is the error term. I cluster standard errors at the PADO event level to allow for an arbitrary variance-covariance structure at the local market level.

Estimates on the lags of entry allow me to identify the dynamics of utilization post-entry, while the leads show utilization prior to entry. Taking the inverse hyperbolic sine of the outcome allows me to interpret effects as approximate percentage changes.[25] The time period FE remove any common trends over time, while the PADO FE imply that the estimates reflect only changes in utilization from within PADO event variation over time.

For completeness, I also estimate the equivalent DiD regression:

$$\sinh^{-1}(y_{pt}) = \alpha D_{pt} + \gamma_t + \theta_p + \nu_{pt} \tag{2}$$

[25]This is similar to taking the natural log, except that the inverse hyperbolic sine is well-defined at zero. The inverse hyperbolic sine of z is defined as $\sinh^{-1}(z) = \ln(z + \sqrt{z^2+1})$.

where D_{pt} is equal to one in all time periods post-entry, ν_{pt} is the error term, and everything else is as defined above. Standard errors are again clustered by PADO event.

The empirical approach in equations 1 and 2 allows public healthcare utilization to differ across locations but critically assumes that – absent PADO entry – trends in utilization would be similar across local markets. The estimates on the leads in equation 1 are a partial test on whether there were any observable differences prior to PADO entry and help validate this strategy.

Threats to identification. The main identifying assumption is that in the absence of PADO entry, trends in utilization across locations would have been similar. Given the inclusion of unit and time FE, the main source of bias stems from unobserved time-varying factors. One particular issue, especially for ARIs, is the possibility of differential seasonality by location. As a robustness check, I construct latitude-longitude grid cells using degrees only and include cell-month FE in equation 1.

A growing literature has identified potential problems with the staggered-timing DiD approach. Goodman-Bacon (2021) shows that the estimator in two-way fixed effects (TWFE) regressions, such as equation 2, is a weighted average of all possible 2×2 DiD. In this setting, it implies that ordinary least squares (OLS) regressions use PADO events that have not yet occurred as a control for PADO entry, but also incorporate PADO entries that have already occurred as a control. If ATE are heterogeneous across units and over time, this last comparison may be problematic for identifying treatment effects.

De Chaisemartin and d'Haultfoeuille (2020) further shows that, under strong parallel trends assumptions, the TWFE estimator is a weighted average of all unit-specific treatment effects, where weights may be negative and non-convex when ATE are heterogeneous. The authors propose an estimator that is robust to this issue. As a robustness check, I implement this procedure and report results in the online appendix.

Lastly, as mentioned above in Section 2, due to low state capacity and lax regulations, the government roster of PADOs may be incomplete. This is not a problem for identification if PADOs are missing at random. If, instead, PADOs are less likely to be observed in more isolated jurisdictions with lower state capacity, I would be identifying a lower bound on the true substitution effect, since those areas would likely have a low presence of public healthcare facilities, leading to a higher amount of substitution with PADO entry. Ultimately, the key is that each PADO event analyzed in the data is a true entry.

3.3 Results

I present event study estimates with six four-week periods on either side of entry, and include indicators for all remaining periods before and after this window. Point estimates are interpreted relative to the four weeks before the event (the excluded period). All results are shown graphically with bars representing 95% confidence intervals.

Outpatient clinic visits. Figure 3 shows the effects on public outpatient clinic visits for ARIs. The first graph considers the baseline specification. Prior to entry, point estimates are relatively flat and statistically insignificant. After entry, there is a gradual and significant decline in utilization. On average, this effect amounts to a 1.7% decline in outpatient visits for ARIs and up to 2.7% 24 weeks after PADO entry. Given the average number of visits, this implies between 21 and 33 fewer visits per week per clinic for ARIs on average.

The remaining plots in Figure 3 explore robustness checks with very similar results. First, I include longitude-latitude cell flexible seasonality controls to account for regional epidemiological trends. Second, I weight regressions by the number of matched clinics, effectively up-weighting larger markets (i.e., those that are served by more public clinics). Third, I use inverse-distance weighted aggregates of ARI visits, so that nearby clinics contribute more to the measure of ARIs in the local market. Fourth, I include always-treated and nevertreated units by including PADO entries that occurred before 2005 and after 2015. Lastly, I construct ARI visit aggregates from clinics that are only within 2.5 km of the PADO.

I do not observe utilization at private facilities (including PADOs). Hence, I cannot say anything about new ARI visits (substitution away from no medical care). The identified effect is thus what happens to public clinic visits in a local market with a PADO entry relative to what would have occurred without that new PADO. Since the public clinics matched with the focal PADO may have already been matched with another previous PADO entry, the counterfactual is not necessarily an absence of PADOs for individuals in these areas, but the introduction of an *additional* PADO. Therefore, I identify the average marginal effect of PADO entry regardless of the base number of PADOs in the surrounding area. Since treatment effects may vary by overall PADO presence, I show estimates robust to heterogeneous ATE in the online appendix (and discuss them below).

Furthermore, using information on the average entry rank for the matched clinics for each PADO, online appendix Figure A3 shows that effects are increasing with average rank. However, due to the correlation between entry rank and time (i.e., later PADO entries are more likely to occur in areas that have already experienced other entries), this may simply reflect an increasing effect over time due to, for example, more competition between PADOs.

Lastly, and for completeness, Table 2 presents DiD estimates from equation 2. Panel A zooms in on a two-year window around entry (with a smaller window for PADO entries in the first and last year of the sample period due to data availability). Panel B uses the full dataset. The first five columns in Table 2 show different specifications for the outpatient visits outcome. Estimates range from a 0.8 to 1.5% decline in ARI visits after PADO entry. Most estimates are statistically significant.

SSA ER visits. The first graph in Figure 4 shows the event study for SSA ER visits due to ARIs. Point estimates are close to zero and insignificant for the weeks leading up to PADO entry, and negative (and quite large) for the weeks after the event. On average, the estimates show a 50% decline in ER visits for ARIs after PADO entry. This amounts to a little over 12 fewer ER visits per week. The analogous DiD results in the next-to-last column of Table 2 show a significant 51-70% decline in ER visits for ARIs after PADO entry.

SSA hospital admissions. The first graph in Figure 5 shows the event study for SSA hospital admissions due to ARIs. Point estimates fluctuate around zero and are mostly insignificant for the weeks leading up to PADO entry. This is followed by a significant decline in ARI admissions. On average, the estimates correspond to an 11.9% decline in hospitalizations after entry. This amounts to about one fewer ARI hospitalization every 14 weeks. The analogous DiD results in the last column of Table 2 are weaker: the point estimate is very small and insignificant when considering only up to two years around entry, and there is a 9% decline that is significant at the 90% level when using the full sample.

Discussion. The estimated impacts of PADO entry on ARI utilization show a significant but relatively small decline in public outpatient clinic visits, a large and significant decline in ER visits, and weaker evidence of a decrease in ARI hospital admissions. This suggests that PADOs are significantly changing how individuals utilize public healthcare, reducing potentially wasteful ER visits, and perhaps decongesting crowded public facilities.

Unfortunately, there are no high-frequency disaggregated data that would allow for estimating effects on overcrowding at these public facilities. However, I shed some light on this by exploiting three rounds of the ENSANUT to estimate the association between PADOs per capita and waiting times at public clinics. Although noisily estimated, results in online appendix Table A5 suggest that PADOs are associated with a large decline in waiting times at public clinics. On average, an additional PADO per 10,000 people is associated with a reduction in waiting times of 44 minutes per visit. Furthermore, there is suggestive evidence of a slight increase in the time public doctors spend with their patients. Since these potential changes in the public sector may lead to overall increases in doctor visits, I also explore this question in the ENSANUT. Point estimates are very small and insignificant, suggesting – if anything – a half percentage point or 1.6% increase in the probability of seeking medical care when sick. However, these data may not be sufficient to fully answer this question.

A key issue for interpreting the ARI utilization results is understanding whether PADO entry is leading to changes in resources and infrastructure of public healthcare facilities. I explore differential changes in physician labor supply using national survey data in online appendix Table A6. Overall, I find no significant associations between PADO presence and the number of doctors, including total doctors, general practitioners, and doctors employed in the public sector. Point estimates, however, are positive for total doctors and negative (and smaller) for doctors in the public sector. These results suggest that, at least in this time frame, PADOs were not significantly affecting the availability of medical staff.[26]

To further complement these findings, I explore a separate dataset where I observe infrastructure (i.e., healthcare facilities) and resources (i.e., medical staff) for all municipalities in Mexico on a yearly basis. Online appendix Table A7 shows insignificant negative associations between PADO presence and both healthcare units and staffing. For the latter, point estimates are below 3%. Given the average PADOs per 10,000 and the average staffing, this effect would imply on average 0.03 fewer medical personnel. These data do show a significant decline in total patient visits, echoing the previous results. This exercise confirms the notion that public healthcare resources are mostly fixed during the study period.

Additional checks on the main ARI results are shown in the online appendix. To further validate the event study design, Figure A4 shows DiD estimators that are robust to heterogeneous ATE (De Chaisemartin and d'Haultfoeuille, 2020). The results for outpatient visits are noisier, but there is a clear and steep decline post-entry. The estimates for ER visits are somewhat larger than those in the event study plot. Lastly, the evidence on hospital

[26] These findings do not answer the question of how these PADOs are being staffed. It is possible that PADOs are simply pulling doctors away from other private sector options. It is also possible that PADOs hire doctors that would have worked at rural public clinics (FUNSALUD, 2014), which would be difficult to observe in the survey data used in Table A6 because of an underrepresentation of rural areas. Survey results suggest that PADO doctors tend to have fewer years of experience and are less likely to have post-graduate studies, but are not significantly different on other markers such as scores on a national standardized exam and the likelihood of having successfully earned their medical degree (Díaz-Portillo et al., 2015).

admissions is less robust, suggesting that there may be no significant effects of PADO entry on this outcome. Lastly, Figure A5 shows permutation tests, randomly shuffling entry dates across PADOs, with point estimates that are all very close to zero.

4 Effects on Utilization for Other Conditions

I turn to estimating event studies for other conditions to better understand the effect of PADO entry on public healthcare use. I focus on three additional conditions: pneumonia, GIDs, and chronic conditions. I also present estimates for all conditions, including a variety of less common diagnoses.

Pneumonia. The first plot in Figure 6 shows the results for pneumonia outpatient visits.[27] Most estimates are statistically indistinguishable from zero and there is no clear pattern, suggesting that PADO entry is not changing utilization for pneumonia at the outpatient level. If pneumonia is a proxy for severe ARIs, this may suggest that ARIs seen at PADOs are less severe on average. The second graph in Figure 4 shows a significant decline in SSA ER visits for pneumonia following PADO entry. The average impact is around 26% fewer ER visits. Lastly, the second graph in Figure 5 shows a gradual and significant decline in pneumonia hospitalizations.

GIDs. The second plot in Figure 6 shows estimates for GID visits at public outpatient clinics. Estimates are mostly zero and insignificant, suggesting no changes in GID visits. The third graph in Figure 4 shows a significant decline in SSA ER visits for GIDs after PADO entry, with an average effect of 46%. Lastly, the third graph in Figure 5 shows a strong pre-trend in GID admissions, which suggests a null impact on GID hospitalizations.

Chronic conditions. The third plot in Figure 6 depicts coefficients for visits due to chronic conditions at public outpatient clinics. Estimates are zero and insignificant prior to entry,

[27] These data are only available from 2007 to 2014.

but there is a significant increase of around 1% post-entry. Although some of the estimates are noisy, the upward trend in chronic disease visits is clear. The fourth graph in Figure 4 shows perhaps a small decline in SSA ER visits for chronic conditions after PADO entry, although estimates are not significant. Lastly, the fourth plot in Figure 5 presents a pre-trend similar to GID admissions, again suggesting a null impact on chronic disease admissions at SSA hospitals.

All conditions. The estimates for all visits and hospitalizations echo the ARI results. There is a significant decline in total outpatient visits (Figure 6, fourth graph) and a large and significant decrease in SSA ER visits (Figure 4, last graph). Lastly, I estimate a noisy and mostly insignificant dip in total hospital admissions (Figure 5, last graph).

Discussion. These estimates indicate important changes in utilization patterns of SSA ER visits after PADO entry for most conditions analyzed. Although there are no significant impacts on outpatient visits for pneumonia and GIDs, there are significant declines in ER visits, which may suggest better management of disease spells or that PADOs are diverting non-emergent patients away from the ER.

Furthermore, I estimate a significant increase in outpatient visits for chronic conditions, with slight declines in ER visits. This positive spillover may allow patients to better monitor their chronic diseases at public clinics after PADO entry, although there are no effects on hospital admissions, which is a common marker of better management of chronic conditions. Nevertheless, the associations with waiting times at public clinics (online appendix Table A5) do suggest that PADOs are increasing access for chronic disease patients by pulling (non-pneumonia) ARI patients away from these clinics.

De Chaisemartin and d'Haultfoeuille (2020) estimators that are robust to heterogeneous ATE are shown in the online appendix. Figure A6 echoes the findings for outpatient visits presented in Figure 6. Figure A7 shows similarly strong effects for SSA ER visits. Lastly,

Figure A8 suggests that there are no significant impacts on hospital admissions. Overall, these estimates corroborate the findings described by the event study plots.

5 Potential Costs from Prescribing Behavior for Antibiotics

Thus far, I have shown that PADO entry leads to declines in public clinic and ER visits for ARIs. There are also sizable reductions in ER visits for other infections. Lastly, clinic visits for chronic conditions increase after PADO entry, consistent with decongestion effects at public clinics. Although effects on hospitalizations are mostly insignificant, these estimates may suggest that PADO expansion is welfare-enhancing by reallocating patients across facilities by diagnosis and increasing access to public healthcare for chronic disease patients.

However, there may be additional costs imposed by PADOs due to lax regulations and misaligned financial incentives due to PADO doctors being pharmacy employees and more generally the vertical integration with the private pharmacies. This section explores one possible cost in the form of changes in the types of antibiotics prescribed, which I broadly associate with quality of care. The goal is not to provide an exhaustive analysis of potential downsides of PADO expansion, but to illustrate one particular trade-off of the positive impacts on access documented above.

5.1 Case Study: Revisiting the Medium-Sized PADO Chain

To further motivate this exercise, I revisit the patient-level data from the anonymous medium-sized PADO chain introduced in Section 2. I identify antibiotic prescriptions for each patient visit and classify them based on nine major antibiotic classes.

I begin by estimating the relationship between diagnoses and being prescribed an antibiotic by regressing an indicator for the latter on indicators for each diagnostic group, with doctor and monthly date FE. The estimates – with 95% confidence intervals and shifted by the sample mean – are shown in the top right plot of Figure 2. Even after accounting for physician-specific practices and overall time trends, over 60% of ARI visits are prescribed an antibiotic. With a few exceptions, other diagnoses have a less than 30% chance.

I further disaggregate ARIs into seven diagnoses. The probability of an antibiotic prescription is high across the board, with an over 50% chance of getting an antibiotic for the common cold (bottom left graph of Figure 2). For reference, less than 5% of common colds are caused by bacteria (see, for instance, Makela et al. 1998).

Lastly, I focus on visits with an antibiotic prescription and regress an indicator for each class on an indicator for ARIs, with doctor and monthly date FE. Conditional on an antibiotic being prescribed, broad spectrum penicillin is given about a third of the time (bottom right graph of Figure 2). Other strong antibiotics, such as cephalosporins and macrolides, also have a relatively high chance of being prescribed (another third when combined).

These associations exemplify how PADO doctors may prescribe antibiotics quite often and are likely to prescribe stronger classes, particularly for ARIs. This motivates the exploration of how antibiotics sold at private pharmacies may change with PADO expansion.

5.2 Data

I obtain detailed, disaggregated sales data at private pharmacies for all class J01 penicillins on a monthly basis from 2010 to 2012.[28] This information is compiled by Knobloch Group (KG), the leading pharmaceutical marketing data firm in Mexico.[29] The data records the product name (at the SKU level), dosage-units sold,[30] and total revenue at the city level. I calculate average prices dividing revenue by units sold, and impute product-month-year-specific aver-

[28]The public system has its own set of public pharmacies that are not included in these data. Some patients visiting a public clinic may also decide to pay out-of-pocket for medications at private pharmacies, due to shortages and waiting times (ENSANUT 2012).

[29]Many pharmaceutical firms in Mexico use KG data, and anecdotal evidence from pharmaceutical company leaders suggests that their information is very reliable. I was able to purchase a small subsample of their data, which is why I limit this analysis to three years and to penicillin only.

[30]KG normalizes sales volume to dosage-units. Based on common physician prescription practices, this number represents units sold for a full course of treatment. All medications in Mexico are sold in a prepackaged format (that is, like a box of Advil in the US).

ages for periods with no sales.[31] Matching publicly available records from COFEPRIS, I assign the chemical composition and manufacturer to each penicillin product.[32] I also map cities in the KG data to municipalities and add municipality-level counts of private pharmacies from the 2009 economic census. I further identify "large" pharmacies, defined as retail pharmacy chains that also sell non-pharmaceutical products (such as CVS in the US). Lastly, I construct a balanced panel of 183 products $\times$ 563 municipalities $\times$ 36 months.

5.3 Empirical Strategy

Distinguishing between types of penicillin. Among infections, and especially ARIs, penicillin is still the most prevalent antibiotic prescribed. There are two main types: narrow and broad spectrum. The former is a more basic antibiotic that is active against specific bacteria types, while the latter acts on a wider range. Due to the risk of increasing bacterial resistance, organizations like the WHO warn against prescribing stronger antibiotics – including broad spectrum penicillin – as a first course of action (Leung et al., 2011). Guidelines from the Mexican government also warn against indiscriminate use of stronger classes.[33]

Descriptive statistics. Table 3 shows summary statistics for the KG data. I distinguish between municipalities that have at least one PADO during the 2010-2012 period and those that do not. Although this is a balanced panel, I show the number of products with positive sales per municipality over this three-year period, as well as the share of these products that are narrow spectrum penicillin. On average, there are more broad spectrum penicillin units sold than narrow spectrum, although conditioning on products that have non-zero sales in each municipality yields very similar numbers for both types. Broad spectrum penicillin is almost three times more expensive than the narrow type. Comparing by PADO presence,

[31] For the imputation, I hold the product and time period fixed and assign the state-level average price. If this is also unobserved, then I assign the countrywide average at the product-period level.

[32] From 194 different products, I drop 11 that are either not commonly used for ARIs or are specifically indicated for very severe or specific bacterial infections. Results are robust to including these products.

[33] See, for example, http://www.cenetec.salud.gob.mx/descargas/gpc/CatalogoMaestro/073_GPC_Faringoamgaguda/Faringo_ER_CENETEC.pdf, last accessed November 5, 2019.

municipalities with PADOs tend to have more types of products sold, more units sold, and a bigger share of large pharmacies, even though price differences are nonexistent.

Empirical strategy. I restrict attention to municipality-product pairs with non-zero sales during the whole three-year period, although results are qualitatively similar when using the entire balanced panel. I estimate the following equation:

$$\sinh^{-1}(q_{amt}) = \zeta_1(PPC_{mt} \times \mathbb{1}_{[a=\text{narrow}]}) + \zeta_2(PPC_{mt} \times \mathbb{1}_{[a=\text{broad}]}) + \gamma_t + \lambda_m + \kappa_a + \eta_{amt} \quad (3)$$

where $\sinh^{-1}(q_{amt})$ is the inverse hyperbolic sine of units sold of penicillin product a in municipality m in year-month t, PPC_{mt} is the number of PADOs per 10,000 individuals, $\mathbb{1}_{[a=\text{narrow}]}$ is an indicator for whether product a is a narrow spectrum penicillin, $\mathbb{1}_{[a=\text{broad}]}$ indicates a broad spectrum penicillin, γ_t are year-month FE, λ_m are municipality FE, κ_a are product FE, and η_{amt} is the error term. I cluster standard errors at the municipality level.

The coefficients of interest are given by ζ_1 and ζ_2, as they represent the average change in units sold for narrow and broad spectrum types, respectively, when there is one additional PADO per 10,000. These estimates may be interpreted as causal impacts as long as the increase in PADOs per capita over time is as good as random after conditioning by time period, municipality, and product. Date FE remove any common trends over time in penicillin sales, municipality FE account for time-invariant differences across locations, and product FE account for differences in sales across penicillin products (and brands).

The main identifying assumption is, therefore, that there are no time-variant unobservables at the municipality level that correlate with both the number of PADOs and the sales volume of penicillin. To address potential confounders, additional specifications include a fully flexible differential time trend by product and add municipality-product FE, effectively identifying the coefficients off of variation within a municipality-product pair over time.

Under the possibility that the PADO roster is incomplete due to the government undercounting entrants, then non-classical measurement error may also bias the estimates. Signing this bias is complicated, even supposing that state capacity correlates negatively with the potential error in PADO counts and positively with sales (for instance, because it correlates with a higher demand for healthcare).

Moreover, identification in the staggered timing DiD with a continuous treatment variable defined in equation 3 is further complicated due to potential heterogeneity between the level effect (i.e., going from zero to positive PADOs) and the slope effect (i.e., incremental changes in the number of PADOs) and because comparison groups are a mix of untreated units and those that are treated at different intensities in different moments in time (Callaway et al., 2021). Causal interpretations therefore rely on much stronger parallel trends assumptions. Given this nascent literature, I interpret my estimates as associations between antibiotic sales and PADOs and caution the reader against a causal interpretation.

In light of these issues and in an attempt to provide some support for a causal effect, I also present an IV estimation. I generate municipality-month aggregates, calculating the broad-spectrum share of penicillin sales for each municipality-period, and estimate:

$$s_{mt}^{\text{broad}} = \xi PPC_{mt} + \gamma_t + \lambda_m + \upsilon_{mt} \tag{4}$$

where s_{mt}^{broad} is the share of penicillin sales that are broad spectrum types in municipality m time period t, υ_{mt} is the error term, and everything else is as defined above. I use the number of products in a municipality with positive sales during the sample period as weights.

I estimate this equation by two-stage least squares (2SLS), instrumenting PADOs per capita with the share of large pharmacies in 2009 interacted with indicators for each sample year. Online appendix Figure A9 inspects the first stage graphically by showing the positive correlation between this instrument and PADOs per capita. The identifying assumption is that the share of large pharmacies, as measured in the 2009 economic census, only has an impact on the share of broad spectrum penicillin types sold during 2010-2012 through its impact on the number of PADOs per capita.

5.4 Results

Table 4 presents the estimates for this exercise. The first five columns show coefficients from estimating equation 3, with each column corresponding to a different specification. The baseline result in column one indicates that an additional PADO per 10,000 people is associated with a statistically significant 13% decline in the number of narrow spectrum penicillin products sold at private pharmacies and a 19% increase in broad spectrum types. Given average sales and PADOs per capita, this would indicate an average decline of 2.6% in narrow spectrum penicillin and a 3.9% increase in broad spectrum. In auxiliary regressions, I do not find evidence of a significant change in total penicillin units sold.

The second column adds fully flexible trends by product, while the third column introduces, instead, municipality-product FE and a flexible trend for municipalities with at least one PADO during this period. The fourth column shows the same specification excluding Mexico City – which corresponds to multiple municipalities – from the sample, while the fifth column restricts to municipalities with at least one PADO during the sample period. Results are similar across these alternative specifications.

The last two columns in Table 4 aggregate the data up to municipality-months and use the share of broad spectrum penicillin products sold as the outcome variable. The next-to-last column estimates equation 4 by OLS, showing that an additional PADO per 10,000 is associated with a significant 3.5 percentage point increase in the share of broad spectrum penicillin sold. The last column shows the 2SLS estimate, which is an order of magnitude larger and statistically significant.

Discussion. Taken together, the results in Table 4 suggest that PADO expansion was associated with important shifts in the types of penicillin products sold at private pharmacies, with a larger share of broad spectrum types and a smaller share of narrow spectrum products. Given the price differences in penicillin products (Table 3), this compositional shift is consistent with financial incentives of vertically integrated pharmacies that may be trying to oversell their patients.[34] To the extent that stronger penicillin may be medically unnecessary, more expensive, and could contribute to antibiotic resistance, I interpret these results as suggesting that PADOs offer lower quality of care.

The inclusion of different FE across specifications suggests that this shift is not driven by epidemiological changes. Likewise, the null effects on pneumonia visits at outpatient clinics (Figure 6) would also suggest that this shift is not due to patient selection (i.e., due to patients who have more severe ARIs choosing PADOs over public clinics). Under the assumption that PADO expansion is uncorrelated with supply shortages at public sector pharmacies, these estimates cannot be explained by public sector patients increasing their private pharmacy purchases. Lastly, effects do not appear to be driven by the law enacted in August 2010 prohibiting over-the-counter sales of antibiotics.[35]

However, I cannot directly link the KG data with prescriptions actually made by PADO doctors. Thus, there may be other factors that explain these results, such as changes in the supply of traditional private providers associated with PADO entry. Moreover, I cannot observe dispensing at public pharmacies, which may also confound the estimates. Nevertheless, these results seem to suggest the possibility of additional costs associated with the proliferation of retail clinics (namely, PADOs overselling patients), particularly in a setting with lax regulations and with patients that are being pulled away from public clinics.

6 Conclusion

As new and innovative private-market healthcare providers expand, understanding the tensions at play is crucial, especially in settings where public and private markets coexist. This paper shows that when retail clinics at private pharmacies enter the local healthcare market

[34] Results in auxiliary regressions show that the decline in narrow spectrum penicillin is concentrated in products that have a below-average price (among these types of antibiotics), while the increase in broad spectrum is driven by products with an above-average price.

[35] The impact of this nationwide law would be absorbed by the time FE. Moreover, restricting to pre-law data, results are qualitatively similar, with a 6% decline in narrow spectrum penicillin sales and a 12% increase in broad spectrum types for each additional PADO per capita.

in Mexico, patient visits at public clinics for non-severe ARIs decrease as well as ER visits for a variety of infectious diseases. This appears to decongest public clinics enough for an increase in visits for patients with chronic conditions, hence improving access to healthcare by shuffling patients across facilities. However, there is evidence suggesting that PADOs may be overselling strong antibiotics to ARI patients, which may be indicative of lower quality of care. Taken together, the findings suggest an important trade-off between access and quality as these PADOs expand.

From a policy perspective, these results inform the need for stronger healthcare regulations, particularly focused on monitoring PADO prescription practices due to the vertical integration with the private pharmacies that may provide doctors with incentives to over-prescribe. Furthermore, better coordination or collaboration between the public and private sectors may lead to increases in the welfare-improving elements of PADOs, such as specializing in different diagnoses and better channeling patients to different types of facilities. These insights may have broad applications in other healthcare settings, and even in other contexts where private and public provision coexist.

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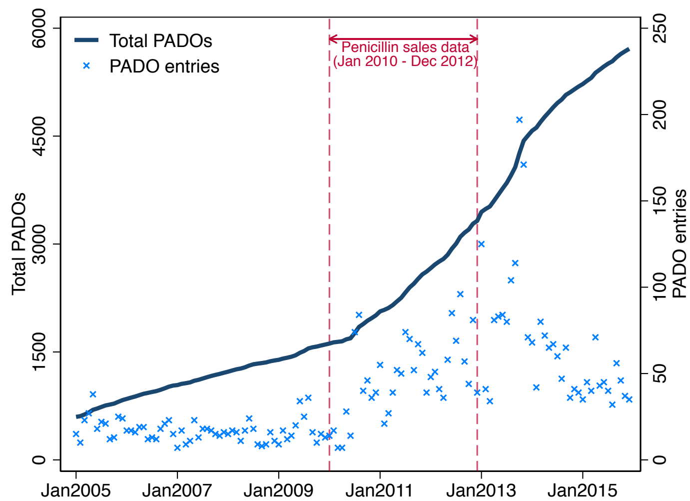
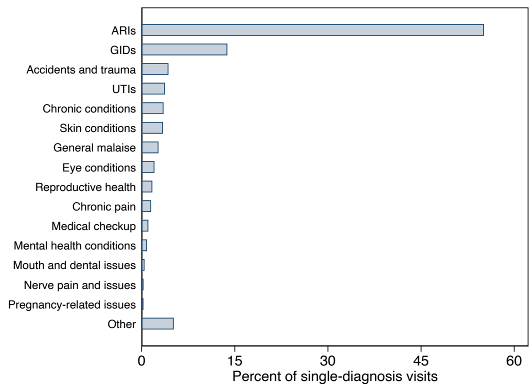
Figures and Tables

Figure 1:
PADO Entry and Cumulative PADOs

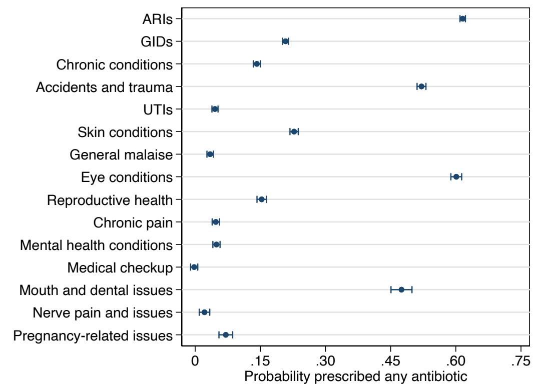


Notes: This graph plots the country-level PADO entries on a monthly basis from 2005 to 2015 (right axis). The solid line shows the cumulative count of PADOs (left axis). Dashed lines denote the time period for which penicillin sales data are available.

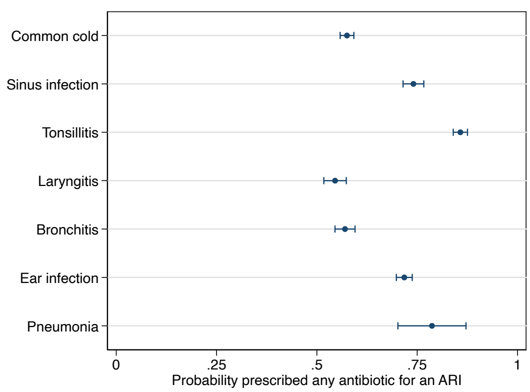
Figure 2:
Diagnoses and Antibiotic Prescriptions at a PADO Chain



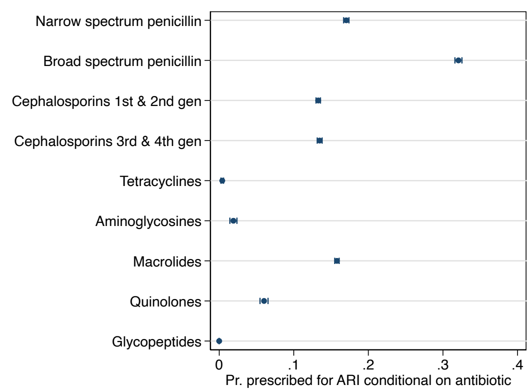
(a) Distribution of diagnoses



(b) Pr(antibiotic) by diagnosis



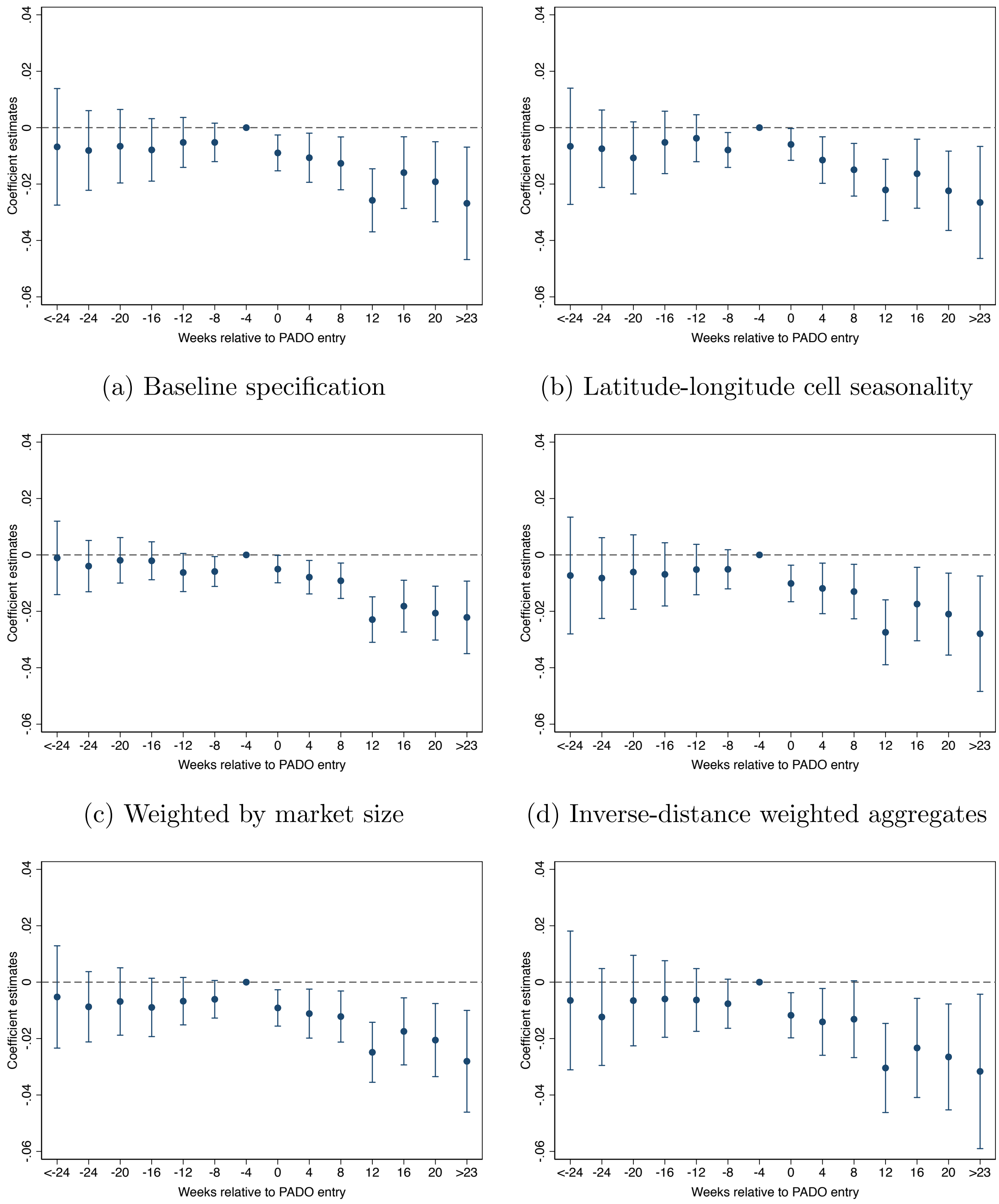
(c) Pr(antibiotic) by ARI diagnosis



(d) Types of antibiotics for ARI diagnoses

Notes: These plots show information from patient records at a medium-sized PADO chain from September 2013 to August 2015. The top left graph shows the distribution of diagnoses for single-diagnosis patient visits. The top right graph shows the probability of being prescribed any antibiotic by diagnosis from regressing an indicator for antibiotics on indicators for each condition, with doctor and month-year FE. The bottom left graph zooms in on types of ARI diagnoses. The bottom right graph shows the probability of being prescribed each type of antibiotic for an ARI conditional on being prescribed an antibiotic, net of doctor and month-year FE. Bars in the last three graphs correspond to 95% confidence intervals from robust standard errors.

Figure 3:
Public Outpatient Clinic Visits for ARIs and PADO Entry



(a) Baseline specification

(b) Latitude-longitude cell seasonality

(c) Weighted by market size

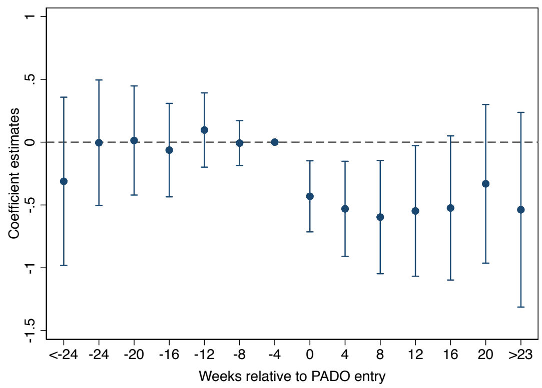
(d) Inverse-distance weighted aggregates

(e) Including all PADO entries

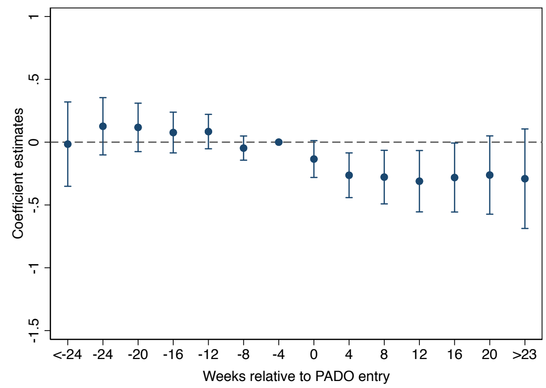
(f) Aggregates within 2.5 km of PADO

Notes: These plots show event studies of PADO entry on public outpatient clinic visits for ARIs (5,111 events from 2005 to 2015). Each PADO is matched with public outpatient clinics within a 5 km radius to construct aggregates of outpatient visits. Each graph shows the coefficients from regressing the inverse hyperbolic sine of visits on a vector of leads and lags of PADO entry, with PADO and time period FE. Robust standard errors are clustered at the PADO level and 95% confidence bars are shown.

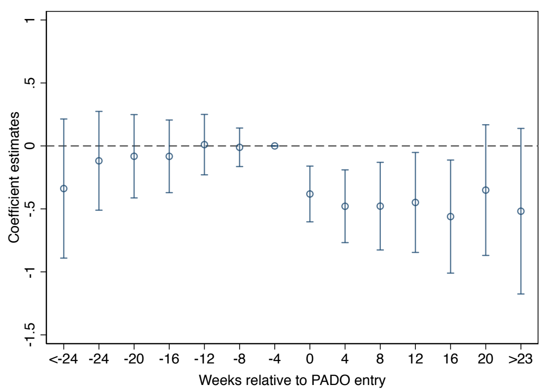
Figure 4:
SSA Emergency Room Visits and PADO Entry



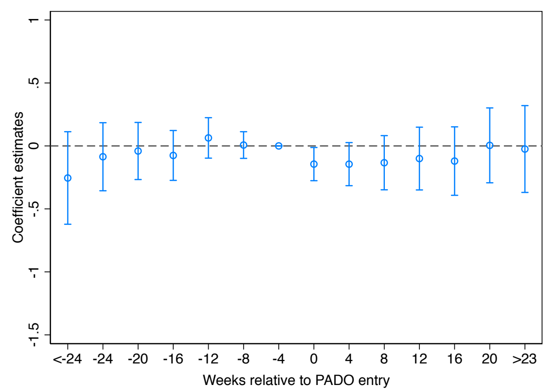
(a) ARIs



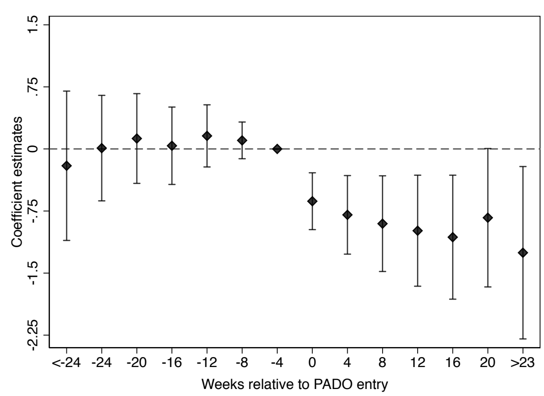
(b) Pneumonia



(c) GIDs



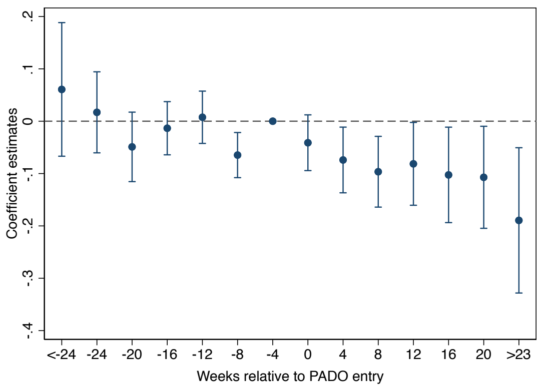
(d) Chronic conditions



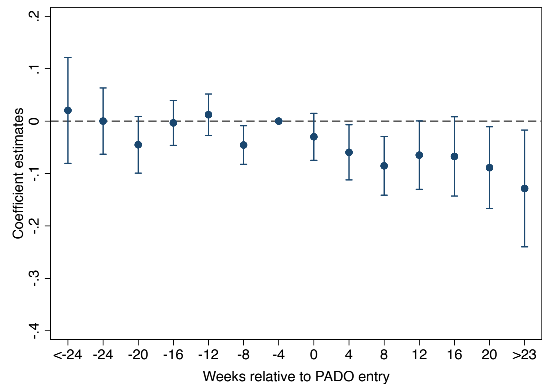
(e) All diagnoses

Notes: These plots show event studies of PADO entry on SSA emergency room visits by diagnosis (157 events from 2008 to 2015). Each PADO is matched with SSA emergency rooms within a 5 km radius to construct aggregates of emergency room visits. Each graph shows the coefficients from regressing the inverse hyperbolic sine of visits on a vector of leads and lags of PADO entry, with PADO and time period FE. Robust standard errors are clustered at the PADO level and 95% confidence bars are shown.

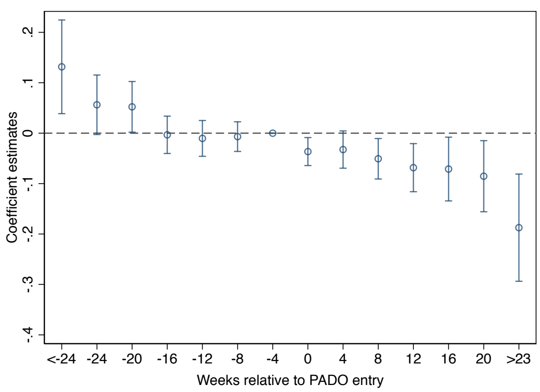
Figure 5:
SSA Hospital Admissions and PADO Entry



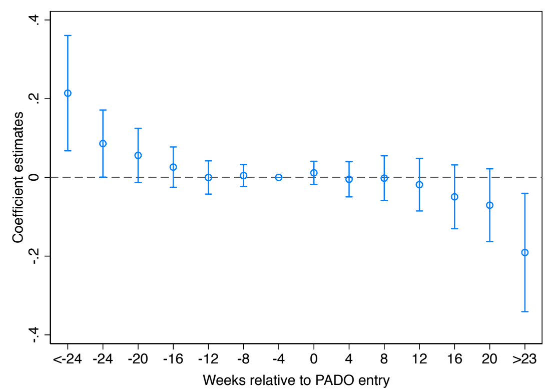
(a) ARIs



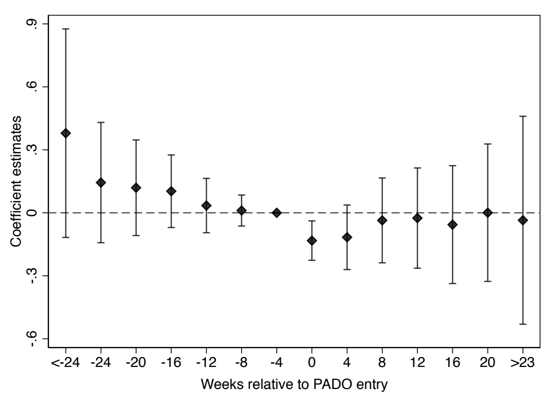
(b) Pneumonia



(c) GIDs



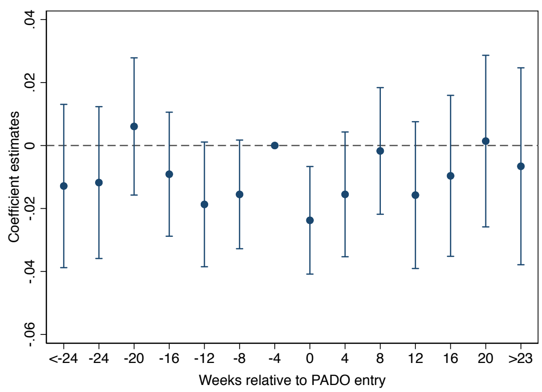
(d) Chronic conditions



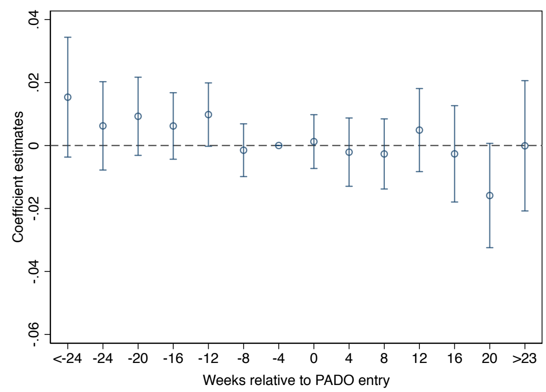
(e) All diagnoses

Notes: These plots show event studies of PADO entry on SSA hospital admissions by diagnosis (444 events from 2005 to 2015). Each PADO is matched with SSA hospitals within a 5 km radius to construct aggregates of hospital admissions. Each graph shows the coefficients from regressing the inverse hyperbolic sine of admissions on a vector of leads and lags of PADO entry, with PADO and time period FE. Robust standard errors are clustered at the PADO level and 95% confidence bars are shown.

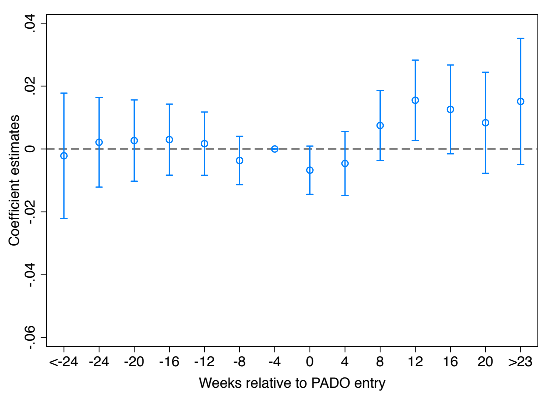
Figure 6:
Public Outpatient Clinic Visits for Other Conditions and PADO Entry



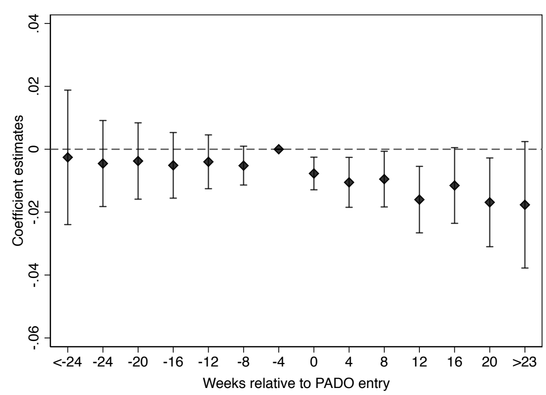
(a) Pneumonia (2007-2014)



(b) GIDs



(c) Chronic conditions



(d) All diagnoses

Notes: These plots show event studies of PADO entry on public outpatient clinic visits for other conditions and diagnoses (5,111 events from 2005 to 2015). Each PADO is matched with public outpatient clinics within a 5 km radius to construct aggregates of outpatient visits. Each graph shows the coefficients from regressing the inverse hyperbolic sine of visits on a vector of leads and lags of PADO entry, with PADO and time period FE. Robust standard errors are clustered at the PADO level and 95% confidence bars are shown.

Table 1:
Descriptive Statistics for Healthcare Utilization

	mean	sd	p5	p50	p95
Panel A: Public Outpatient Clinics					
Number of matched clinics	14.30	11.03	2.00	12.00	35.00
Average entry rank for matched clinics	14.88	16.56	1.00	8.56	49.62
Average distance to matched clinics	2.66	0.88	0.72	2.89	3.73
SSA share of matched clinics	0.71	0.20	0.33	0.73	1.00
All clinic visits	7,559.74	8,748.01	247.00	4,083.00	26,126.00
ARI visits	4,811.11	5,810.75	152.00	2,499.00	17,008.00
Pneumonia visits	8.43	19.23	0.00	1.00	41.00
GID visits	953.27	1,139.29	21.00	503.00	3,345.00
Chronic disease visits	518.82	619.49	12.00	267.00	1,858.00
Observations	730,873	730,873	730,873	730,873	730,873
PADO events (2005-2015)	5,111	5,111	5,111	5,111	5,111
Panel B: SSA Emergency rooms					
Number of matched ERs	1.00	0.00	1.00	1.00	1.00
Average distance to matched ERs	2.46	1.45	0.28	2.76	4.74
All ER visits	466.95	682.98	0.00	80.00	1,781.00
ER visits for ARIs	98.20	183.16	0.00	1.00	472.00
ER visits for pneumonia	5.94	16.71	0.00	0.00	29.00
ER visits for GIDs	36.91	71.05	0.00	0.00	168.00
ER visits for chronic conditions	10.23	18.95	0.00	0.00	53.00
Observations	16,328	16,328	16,328	16,328	16,328
PADO events (2008-2015)	157	157	157	157	157
Panel C: SSA Hospitals					
Number of matched hospitals	1.02	0.14	1.00	1.00	1.00
Average distance to matched hospitals	2.62	1.40	0.33	2.68	4.71
All hospital admissions	96.40	133.53	0.00	26.00	403.00
Hospital admissions for ARIs	2.35	6.83	0.00	0.00	14.00
Hospital admissions for pneumonia	1.45	5.46	0.00	0.00	9.00
Hospital admissions for GIDs	1.00	2.39	0.00	0.00	6.00
Hospital admissions for chronic conditions	1.98	4.26	0.00	0.00	12.00
Observations	63,492	63,492	63,492	63,492	63,492
PADO events (2005-2015)	444	444	444	444	444

Notes: This table shows the mean, standard deviation, median, and the 5th and 95th percentiles of variables related to healthcare utilization. Each panel corresponds to a mapping from PADO entry events to healthcare utilization. Observations are at the PADO-by-time-period level, where a time period is a four-week interval from 2005 to 2015 for the outpatient clinics and SSA hospital matches and from 2008 to 2015 for the SSA ER matches.

Table 2:
DiD Effect of PADO Entry on Public Healthcare Utilization for ARIs

	Public outpatient clinics						
	Base spec.	Incl. PADO events post-2015	Incl. lat.-lon. grid cell seasonality	Inv.-dist. weighted aggregates	Aggregates within 2.5 km	SSA ERs base spec. (2008-15)	SSA hosp. base spec.
Panel A: up to 2-year window around entry							
After entry	-0.0099**	-0.0098**	-0.0084*	-0.0116***	-0.0110*	-0.7022***	-0.0023
	(0.0044)	(0.0044)	(0.0043)	(0.0045)	(0.0062)	(0.2109)	(0.0294)
Observations	438,552	460,964	438,552	438,552	420,111	12,689	38,312
R-squared	0.9555	0.9564	0.9587	0.9538	0.9286	0.5473	0.6735
Mean dep. var.	4,940	4,998	4,940	5,107	1,868	106.3	1.93
Panel B: full sample							
After entry	-0.0115	-0.0112	-0.0110	-0.0129*	-0.0150*	-0.5128**	-0.0918*
	(0.0074)	(0.0069)	(0.0074)	(0.0075)	(0.0090)	(0.2541)	(0.0484)
Observations	730,873	822,965	730,873	730,873	700,414	16,328	63,492
R-squared	0.9374	0.9379	0.9404	0.9355	0.9040	0.5154	0.6155
Mean dep. var.	4,811	5,009	4,811	4,967	1,808	98.2	2.31

Notes: This table shows the DiD effect of PADO entry on healthcare utilization for ARIs at public outpatient clinics (first five columns), SSA ERs (sixth column), and SSA hospitals (last column). Panel A restricts the data to (up to) a two-year window centered around PADO entry. Panel B uses the full data. Outcomes are all transformed with the inverse hyperbolic sine. The base specification regresses the outcome on an indicator for post-entry, with PADO and time period FE. The second column also includes PADO events occurring after 2015. Column 3 adds latitude-longitude grid cell seasonality controls. Column 4 uses inverse-distance weighted aggregates of the matched clinics. Column 5 restricts to matched clinics within 2.5 km of the PADO. Robust standard errors clustered at the PADO level are shown in parentheses. The mean dependent variable in levels is reported.
*** p<0.01, ** p<0.05, * p<0.1

Table 3:
Descriptive Statistics for Penicillin Sales Data

	All municipalities	Muns. with PADO entry	Muns. without PADOs
Number of different products sold	69.31	77.26	48.94
	(26.83)	(25.38)	(18.33)
Share of narrow spectrum penicillin products	0.63	0.63	0.61
	(0.48)	(0.48)	(0.49)
Narrow spectrum penicillin units sold	10.31	13.72	1.56
	(177.49)	(209.03)	(12.03)
Narrow spectrum units | non-zero sales	31.00	36.79	6.81
	(306.74)	(341.01)	(24.43)
Broad spectrum penicillin units sold	13.97	18.77	1.67
	(93.72)	(109.97)	(9.42)
Broad spectrum units | non-zero sales	29.87	36.55	4.76
	(135.29)	(151.30)	(15.46)
Narrow spectrum penicillin price	46.02	46.02	45.99
	(35.89)	(35.92)	(35.82)
Broad spectrum penicillin price	126.72	126.87	126.33
	(92.99)	(93.16)	(92.56)
Share of large pharmacies	0.11	0.14	0.04
	(0.15)	(0.16)	(0.10)
Municipalities	563	405	158
Observations	3,709,044	2,668,140	1,040,904

Notes: This table shows the mean and standard deviation of variables related to penicillin sales. The first column shows all municipalities in the sample, while the second and third column restrict to municipalities with and without PADO entry, respectively. Observations are a balanced panel at the product-municipality-month level from January 2010 to December 2012. Units sold conditional on non-zero sales refers to observing at least one unit sold in a given municipality-product pair during this time period. The share of narrow spectrum penicillin products is conditional on positive sales during this period. Large pharmacies are defined as retail pharmacy chains that also sell non-pharmaceutical products. Data on pharmacies is from the 2009 economic census.

Table 4:
Associations between PADOs and Penicillin Sales

	Full dataset: $y = \sinh^{-1}$(units sold)					Collapsed data: y = share broad spectrum	
	Base spec.	Product-time period FE	Mun.-prod. FE + PADO trend	Excl. Mexico City	Muns. with PADOs only	Base spec.	2SLS
Total PADOs per 10,000 × narrow spectrum	-0.129**	-0.153***	-0.129**	-0.126**	-0.129**		
	(0.061)	(0.059)	(0.059)	(0.059)	(0.059)		
Total PADOs per 10,000 × broad spectrum	0.188***	0.137**	0.193***	0.205***	0.193***		
	(0.058)	(0.057)	(0.048)	(0.048)	(0.048)		
Total PADOs per 10,000						0.035**	0.269***
						(0.015)	(0.102)
Observations	1,381,464	1,381,140	1,381,464	1,333,116	1,106,064	20,160	20,160
R-squared	0.541	0.580	0.797	0.793	0.802	0.724	0.707
F statistic							10.48
Mean dependent variable:							
Narrow spectrum units	31.00	31.00	31.00	28.37	36.79		
Broad spectrum units	29.87	29.87	29.87	26.27	36.55		
Share broad spectrum						0.325	0.325
Mean PADOs per 10,000	0.204	0.204	0.204	0.203	0.284	0.204	0.204
Mean PADOs	3.83	3.83	3.83	3.62	5.32	3.83	3.83

Notes: This table shows estimates of the association between PADOs per capita and penicillin sales. The first five columns use the full data at the product-municipality-time period level, using the inverse hyperbolic sine of units sold as the outcome variable. The last two columns aggregate the data to the municipality-time period level and use the share of units sold that are broad spectrum products as the outcome. The base specification in the first column regresses the outcome on PADOs per capita, with product, municipality, and time period FE. The second column adds product-time period FE. Column 3 instead uses municipality-product FE and includes differential time period FE for municipalities with PADO entry. Column 4 is the same as the third column excluding Mexico City, while column 5 restricts to municipalities with PADOs during this period. For the collapsed data, the base specification includes municipality and time period FE, and the last column shows an IV estimate using the share of large pharmacies interacted with indicators for 2011 and 2012 as instruments for PADOs per capita. Robust standard errors clustered at the municipality level are shown in parentheses. The mean dependent variable in levels is reported, as well as the average number of PADOs. Average narrow and broad spectrum units sold are conditional on having non-zero sales for a given municipality-product pair over the entire period.
*** p<0.01, ** p<0.05, * p<0.1

Appendix for Online Publication

A The Mexican Healthcare System

Organization of healthcare. The Mexican healthcare system is a mix of public and private providers. The public sector is divided into separate institutions based on target population. Each institution has its own set of providers and benefits.

Formal workers, their dependents, and retirees have access to IMSS (Mexican Social Security Institute, *Instituto Mexicano del Seguro Social*). Workers in the informal economy and unemployed individuals have access to healthcare through enrollment in the *Seguro Popular* (SP) program, which is administered by the Ministry of Health (SSA). In addition to these public institutions, 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.

Private insurance is mostly employment-based but only at higher wage levels, and serves as a complement to the legal requirement of IMSS enrollment. This type of insurance can only be used with private providers, and is frequently restricted to catastrophic events (i.e., hospitalizations). Public healthcare coverage, such as IMSS, does not pay for any private-market services.

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. There is generally very low portability of benefits from one public system to the other, and benefit plans vary substantially across institutions.

Healthcare coverage and utilization. Table A1 shows healthcare coverage from the 2012 National Health Survey (ENSANUT). About 73% of the population has access to the public system, with the majority at IMSS and SSA. Less than 1% of the population has private insurance, and about 26% is not covered by any public or private plan.

The 2012 ENSANUT also asks respondents to name their main primary healthcare provider. 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 either self-medicating or not getting medical attention.

Actual utilization is reported in Table A2. These statistics refer to actual outpatient service utilization during the respondents' last sickness spell, conditional on having been sick and seeking medical attention. Regardless of the symptoms, 58% sought medical attention in the public system, while 15% went to a PADO and 23% to a different private provider. This shows a large utilization of private health services in Mexico. Table A2 also breaks down these numbers by type of symptoms.

Healthcare provider and patient characteristics. Table A3 presents descriptive statistics based on utilization of public, PADO and other private outpatient services. Focusing on PADO users, 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 drivers, while knowing the provider and being satisfied with the quality of care provided are the main reasons for choosing other private doctors.

Transportation costs in time and money are significantly lower for PADOs, and also have the lowest waiting times and time spent with doctor. PADO waiting times are around a quarter of the average wait at public institutions, and other 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 main (self-reported) reasons for seeking care at a PADO is that they are near, cheap, and fast. Beneficiaries of the public system are assigned to a clinic based on their registered home address and must seek non-emergent care at that clinic. Hence, it is possible that a PADO may be closer than the assigned facility. The average transportation time and costs for patients going to the public clinics vs PADOs seem to suggest that this is the case. PADOs are also cheaper than other private providers, as stated above, and moreover, may offer an attractive price-performance ratio due to convenience and perceived quality. Lastly, on average, patients wait an hour longer at public clinics than at PADOs. Given the average PADO cost of 39 pesos, it may be worthwhile to choose a PADO, depending on patients' value of time (for example, the hourly minimum wage at the time of the survey was around 60 pesos).

The public system 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. 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.

Additional details on PADOs. Figure A1 shows histograms of PADO entries. The plot on the left shows the full distribution of the number of new entrants each month from 1997 to 2019. The plot on the right shows the within-year distribution of entries. There are large spikes on the first of the month as well as smaller spikes on the 15th of each month. This is possibly due to bureaucrats using round dates to register PADOs. I address this by focusing on four-week periods in the empirical exercise. Figure A2 shows a series of maps with the location of new PADO entries in four different periods over time. The maps all show that entry has always been widespread across the country.

B Classification of Acute Respiratory Infections

All diagnoses are classified using ICD-10 codes. The public outpatient clinic data use a specific definition of what constitutes ARIs. Table A4 lists these codes for ARIs. In the SSA

ER and hospital admissions data, each observation corresponds to a patient. Therefore, ARIs are constructed directly from patient ICD-10 codes, using all classifications from J00 to J22, as is customary in the literature.

C Robustness Checks and Additional Results

Heterogeneity by entry rank of the matched clinics. When matching healthcare units to PADOs within a 5 km radius, some units may be matched to more than one PADO event. To proxy for how novel a PADO is in the local market, I calculate the entry rank for each matched clinic and obtain the average for each PADO event. The first plot in Figure A3 shows the association between this measure and the entry date of the PADO. As expected, there is a positive correlation.

To further understand the effect of PADO entry on utilization by entry rank of the matched clinics, I split the sample by terciles of the average entry rank. I then present event study plots for ARI visits at public outpatient clinics in the remaining graphs of Figure A3. For PADO events in the bottom tercile of average entry rank, I find no significant effect. The impact is relatively small but significant for those in the middle tercile, and large and significant in the top tercile.

This finding may suggest that competition between PADOs is an important feature of their effect on public healthcare utilization. However, given the correlation with time (i.e., higher average rank in later entry dates), it is possible that other explanations hold, such as patients learning over time or increased marketing efforts from pharmacy chains.

DiD estimators robust to heterogeneous ATE. Following the recent literature revisiting the validity of TWFE models for DiD designs (Goodman-Bacon, 2021; Sun and Abraham, 2020), this robustness check implements the estimator presented in De Chaisemartin and d'Haultfoeuille (2020) that is robust to heterogeneous ATE. This exercise helps validate the event study design in the main text.

Figure A4 considers the main results concerning ARI healthcare utilization at public outpatient clinics, SSA ERs, and SSA hospitals. The first plot shows relatively stable estimates around zero prior to PADO entry, with a subsequent gradual decline in outpatient visits for ARIs of up to around 2% by the end of the first year post-entry. The second plot again shows insignificant estimates pre-entry, followed by a sharp decline in ER visits of around 70%. The last plot does not show any strong effects post-entry, particularly given the pre-entry dynamics.

Figure A6 repeats the exercise for other conditions at public outpatient clinics. There do not seem to be particularly salient effects for pneumonia and GIDs, but there does seem to be a gradual increase in outpatient visits that are related to chronic conditions. Overall, visits for all diagnoses also decline post-entry.

Figure A7 shows that the negative impact on ER visits holds for pneumonia, GIDs, and, with a smaller magnitude, chronic conditions. Finally, Figure A8 suggests that there are no significant effects for SSA hospital admissions across the board.

Placebo effects from randomly shuffled dates. As a placebo check, I randomly shuffle the PADO entry dates across PADOs. Using these placebo dates, I estimate an event study as in the main text. I repeat this exercise 1,000 times. Figure A5 shows the average coefficient estimates from this exercise. I consider ARI utilization at public healthcare clinics, SSA ERs, and SSA hospitals. The plots all show estimates that are very close to zero.

Associations with self-reported probability of seeking medical care and service characteristics at public facilities. To shed some light on whether PADOs are associated with an increase in total doctor visits and whether the substitution away from public facilities has effects on the service characteristics at these facilities, I exploit data from the 2006, 2012, and 2018 ENSANUT rounds.

Each survey asks whether individuals that reported being sick in the last two weeks ever sought medical care. I construct an indicator for seeking any type of medical care conditional on being sick. For those that got care at a public facility, I identify the institution or subsystem they visited, how long they had to wait to see the doctor, and how long the doctor spent with them. To deal with large (and implausible) outliers, I trim these time measures at the 99th percentile.

For each individual, I observe their municipality of residence. I use this information to match PADO counts at the municipality-year level. I add municipality-level information from the 2010 census to construct a measure of PADOs per 10,000 individuals. I then regress each outcome on PADOs per capita, including municipality and year FE, and weighting regressions with the survey weights. I cluster standard errors by municipality. All regressions are restricted to individuals ages 18 and over, and to municipalities that are observed at least six times in all survey years. Regressions for the public service characteristics are further restricted to seeking care at a public facility and also include institution FE.

Table A5 shows the results from this exercise. The first column shows the base specification, with subsequent columns adding controls. Diagnosis controls are indicators for each major diagnostic group. Individual controls are socioeconomic characteristics of respondents, including gender, age, whether the person is the household head, indicators for healthcare coverage, whether the person is literate, indicators for education, and an indicator for employment status. Differential trends are linear trends for municipalities that ever have PADOs and linear trends by municipality characteristics in the 2010 census (namely, population, share female, average schooling, share employed, share with healthcare coverage, and share with access to basic services, that is, electricity, piped water, and sewerage).

Panel A shows very small and statistically insignificant estimates for the association of PADOs with the probability of seeking medical care when sick. I interpret these results as indicating that PADOs do not seem to be associated with an overall increase in the probability of receiving medical care. This suggests that PADOs are mostly shuffling patients around, although perhaps this exercise is underpowered.

Panel B shows the inverse hyperbolic sine of waiting times at public clinics. All point estimates are negative and large (upwards of a 50% reduction in waiting times), although only the last column shows a significant coefficient at the 90% level. This suggests that – although quite noisy – PADOs are associated with a sizable decline in waiting times at public clinics, possibly due to the substitution patterns documented in the main text.

Lastly, panel C shows positive and insignificant estimates for time spent with the doctor. The largest point estimate would indicate a 10% increase in duration of consultations, although standard errors are quite large.

Associations with physician labor supply. A key question for understanding substitution patterns is who is staffing the PADOs? Or more specifically, what is happening to overall doctor labor supply with PADO entry? To shed light on this question, I use data from the quarterly national employment survey (ENOE). I collapse observations to the municipality-year-quarter level from 2005 to 2015, and restrict to municipalities that are continuously observed for a balanced panel of 406 municipalities. The survey is more likely to continuously include municipalities with larger labor markets.

I consider various measures of doctor labor supply: (i) total doctors per capita, (ii) general doctors per capita, (iii) specialists per capita, (iv) total public sector doctors per capita, and (v) total public sector doctors that report having more than one employer. I take the inverse hyperbolic sine of these outcomes before regressing on the number of PADOs per 10,000 with municipality and time period FE. I cluster standard errors by municipality.

Table A6 shows the results, with each column corresponding to a different outcome. Panel A shows the base specification, while panel B adds a differential linear trend for municipalities that ever had at least one PADO. None of the estimates are statistically significant at conventional levels. This suggests that, at least in this time period, doctor labor supply is not shifting critically due to PADO entries, and it is therefore unlikely that public clinics are more understaffed when more PADOs enter the market.

Observing the point estimates alone regardless of statistical significance, an additional PADO per 10,000 people would seem to be associated with a 16-18% increase in the number of doctors per capita and a 5-6% reduction in doctors in the public sector. Given the average PADOs and public sector doctors, this last estimate would imply on average a reduction of 0.18 public sector doctors or 1%. This suggests that even if the effect were statistically significant, it is likely to be economically insignificant.

An important limitation of the ENOE data is that the survey tends to oversample from more urban areas. Although PADOs seem to be a predominantly urban phenomenon, there may be important dynamics in the labor supply of doctors at public facilities in urban vs rural areas when PADOs enter the nearest city.

Associations with public healthcare resources and visits. To complement these findings, I exploit data from the State and Municipal System Databases (SIMBAD) from 2007 to 2014. These data are at the municipality-institution-year level, and record infrastructure and utilization data from the public sector clinics at all institutions. Although these are more aggregate data, they allow me to observe almost all municipalities in the country as well as clinic staffing.

I consider three outcomes in this exercise: the number of public outpatient clinics, total medial staff per clinic (including all doctors and nurses), and yearly patient visits per clinic. I take the inverse hyperbolic sine of these outcomes before regressing on the number of PADOs per 10,000 with municipality, institution, and time period FE, as well as a differential linear trend for municipalities that have at least one PADO during this period. I cluster standard errors by municipality.

Table A7 shows the results. Two specifications are shown for each outcome: the baseline regression and the same regression weighted by the number of public outpatient clinics in 2007 (shown in every second column). Estimates are not significant for the impact of PADOs per capita on the number of healthcare units and on healthcare staff. Moreover, these point estimates are relatively small, especially those related to staffing. This suggests that PADOs are not associated with differential changes in staffing at public clinics, echoing the results shown in Table A6.

The last two columns in Table A7 show the association between PADOs per capita and yearly patient visits at public outpatient clinics. These estimates are significant at the 90% level, showing that an additional PADO per 10,000 in a municipality is associated with a 10 to 25% decline in the number of yearly patient visits. This result echoes the main findings in the text.

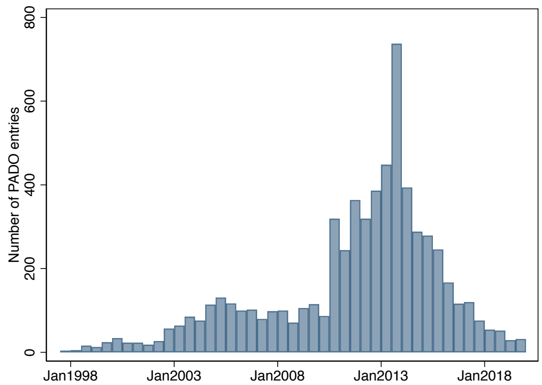
Correlation between share of large pharmacies and PADOs. I present evidence of a strong first stage for the IV estimate presented in the main text. The first plot in Figure A9 shows a binned scatterplot of the share of pharmacies in a municipality that were large pharmacies according to the 2009 economic census against the number of PADOs per 10,000 people during 2010-2012. The plot uses the number of products in each municipality with nonzero sales as weights. I include a line of best fit with a slope coefficient of 0.182 that is significant at the 99% level.

Since the share of large pharmacies is time-invariant (and measured in 2009), the IV regression uses the interaction of this share with year indicators for 2011 and 2012 as the instruments. This effectively allows for a separate slope for each year. I show similar binned scatterplots for these two interactions in the remaining graphs in Figure A9. The slope coefficient for the 2011 interaction is 0.092 and the slope coefficient for the 2012 interaction is 0.385, both of which are strongly significant.

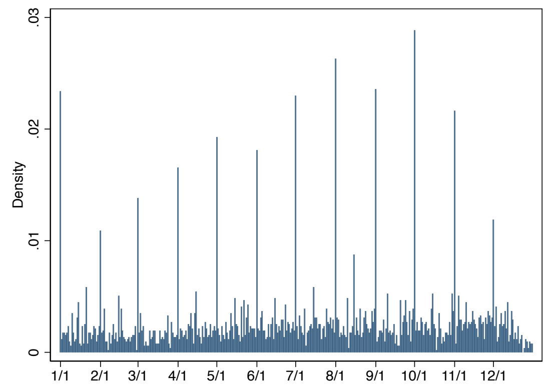
D Time Series of Penicillin Sales

Figure A10 shows the raw data for the penicillin sales. Each series corresponds to a type of penicillin: narrow and broad spectrum. Each plot aggregates the data from a different set of municipalities based on the number of PADOs in December 2012. The top-left graph corresponds to places without any PADOs. The other three plots show terciles of the number of PADOs. For reference, a vertical line shows the introduction of the law in August 2010 that limited over-the-counter sales of antibiotics. Although there seems to be some evidence of a decline in narrow spectrum penicillin sales after the law, there is a considerably large downward trend since early 2010. Furthermore, since this law was implemented nationwide, there is no clear way to construct a counterfactual of antibiotic sales absent the law.

Figure A1:
Histograms of PADO Entries



(a) Distribution of entries 1997-2019

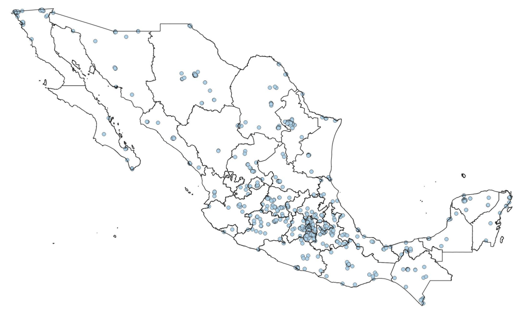


(b) Within year distribution of entries

Notes: These plots show histograms of PADO entries in the data. The left graph shows the number of PADO entries by date from 1997 to 2019. The plot on the right shows the within-year distribution of entries.

Figure A2:
Spatial and Temporal Distribution of PADOs

(a) 1997 to 2004



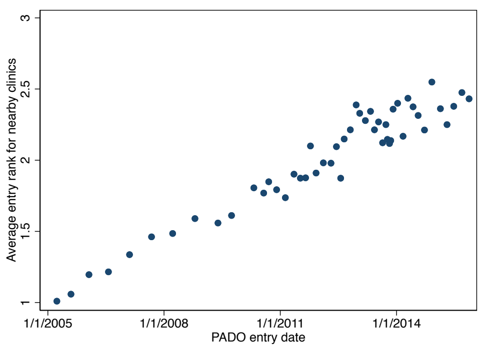
(b) 2005 to 2009

(c) 2010 to 2015

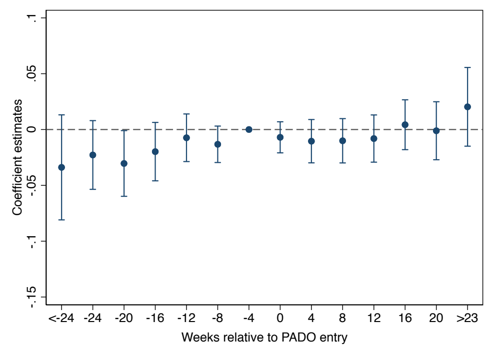
(d) 2016 to 2019

Notes: These maps show the spatial distribution of new PADOs across Mexico by year of entry. The periods 1997-2004 and 2016-2019 correspond to before and after the sample period for the public healthcare utilization outcomes, respectively.

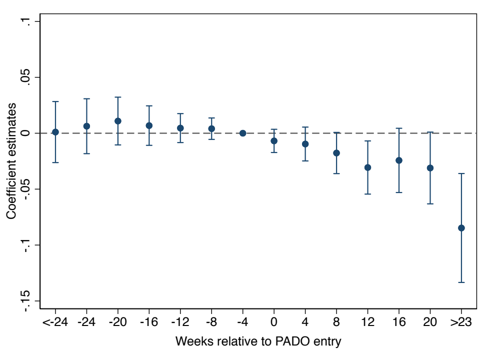
Figure A3:
Entry Rank of Matched Clinics and the Effect of PADO Entry on
ARI Utilization at Public Outpatient Clinics



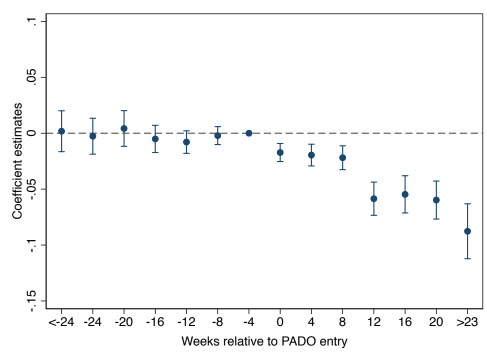
(a) Average rank by entry date



(b) Bottom tercile of average rank



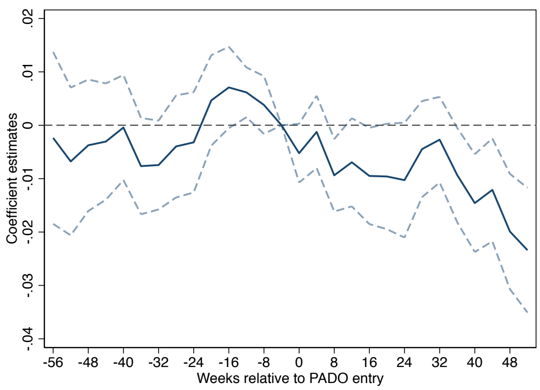
(c) Middle tercile of average rank



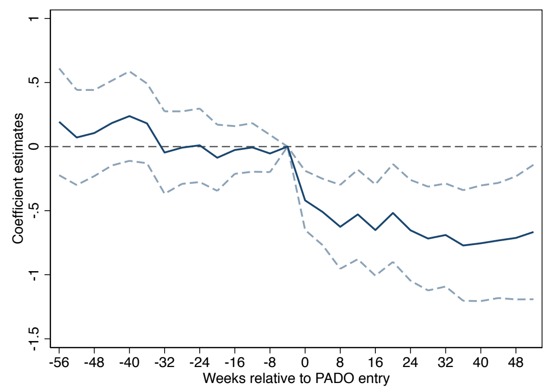
(d) Top tercile of average rank

Notes: These plots show how the effect of PADO entry on ARI utilization at public outpatient clinics varies by the average entry rank of the matched clinics. The plot on the top left shows how the average entry rank grows over time. The remaining plots estimate an event study specification restricting to PADO events in the bottom, middle, and top tercile of the average entry rank, respectively. Each of these graphs shows the coefficients from regressing the inverse hyperbolic sine of ARI visits on a vector of leads and lags of PADO entry, with PADO and time period FE. Robust standard errors are clustered at the PADO level and 95% confidence bars are shown.

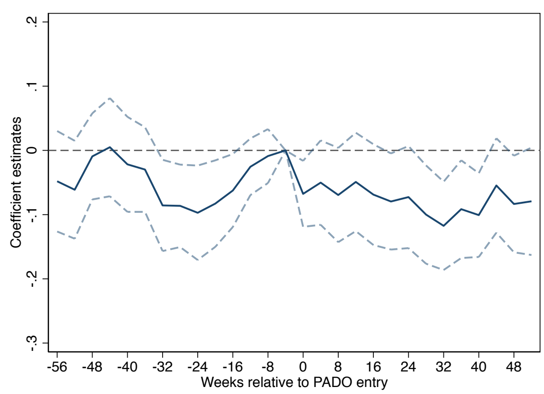
Figure A4:
DiD Estimators Robust to Heterogeneous ATE for Public Healthcare Utilization for ARIs



(a) Outpatient clinic visits



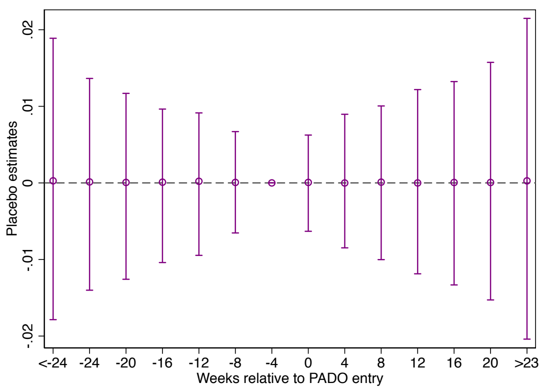
(b) SSA ER visits



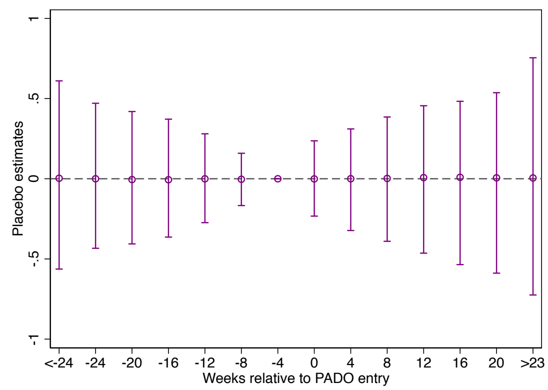
(c) SSA hospital admissions

Notes: These plots show DiD estimators robust to heterogeneous ATE as described in De Chaisemartin and d'Haultfoeuille (2020) for the effect of PADO entry on healthcare utilization for ARIs. PADOs are matched with healthcare units within a 5 km radius to construct aggregates of ARI utilization. Each plot considers lead and lag estimates for a two-year window around entry, controlling for PADO and period FE. Dashed lines represent 95% confidence bands constructed from 100 bootstrap repetitions. The outcome variables are the inverse hyperbolic sine of public outpatient clinic visits, SSA ER visits, and SSA hospitalizations, respectively.

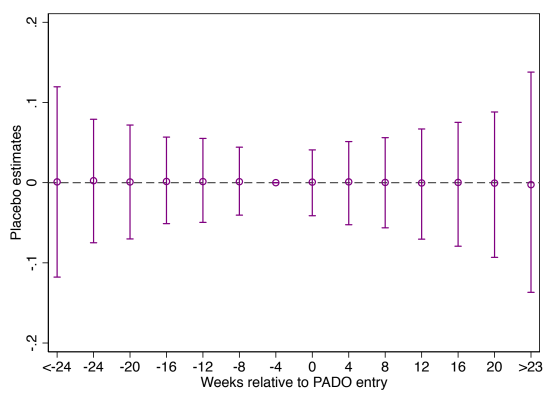
Figure A5:
Placebo Estimates from Randomly Shuffled Entry Dates for
Public Healthcare Utilization due to ARIs



(a) Outpatient clinic visits



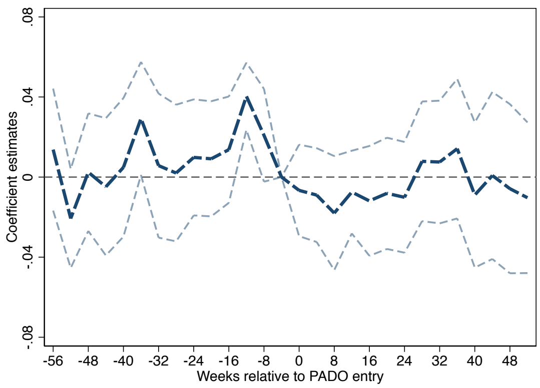
(b) SSA ER visits



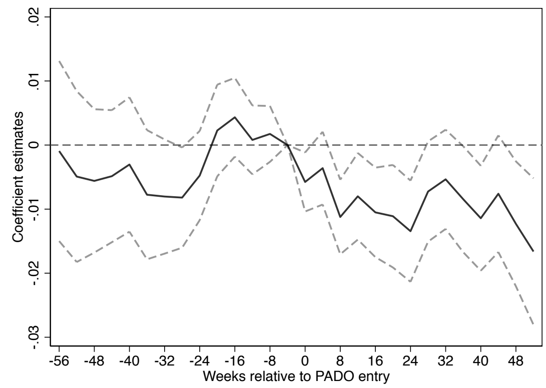
(c) SSA hospital admissions

Notes: These plots show a placebo exercise where PADO entry dates were randomly shuffled across PADOs. The exercise was repeated 1,000 times. For each iteration, I regress the inverse hyperbolic sine of ARI visits or admissions on a vector of leads and lags of PADO entry, with PADO and time period FE, with robust standard errors clustered at the PADO level. The plots show the average coefficient estimates across the 1,000 iterations with 95% confidence bands.

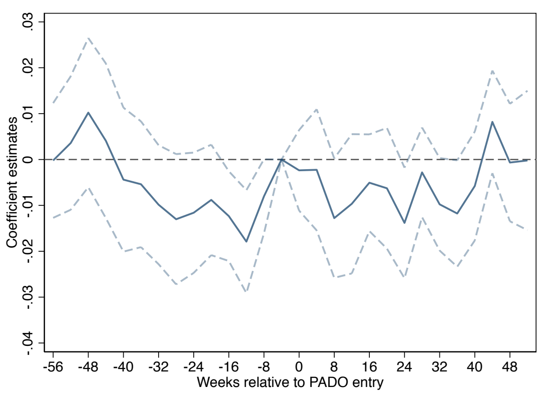
Figure A6:
DiD Estimators Robust to Heterogeneous ATE for Public Outpatient Clinic Utilization for Other Conditions



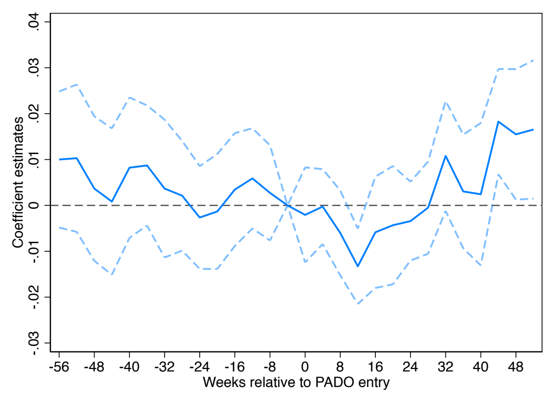
(a) Pneumonia (2007-2014)



(b) All diagnoses



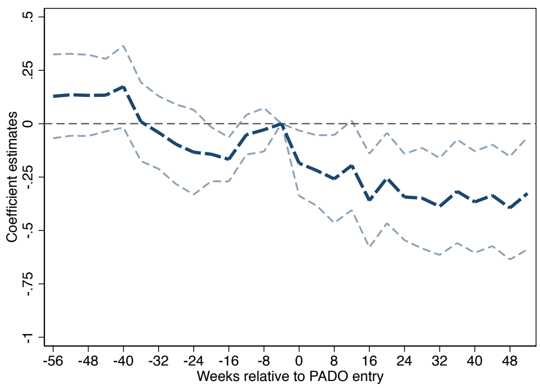
(c) GIDs



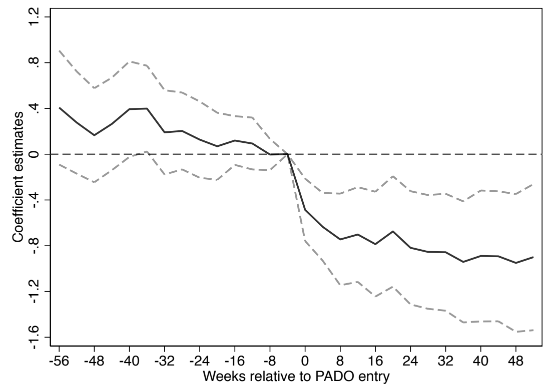
(d) Chronic conditions

Notes: These plots show DiD estimators robust to heterogeneous ATE as described in De Chaisemartin and d'Haultfoeuille (2020) for the effect of PADO entry on public outpatient clinic utilization for conditions different than ARIs. PADOs are matched with outpatient clinics within a 5 km radius to construct aggregates of utilization. Each plot considers lead and lag estimates for a two-year window around entry, controlling for PADO and period FE. Dashed lines represent 95% confidence bands constructed from 100 bootstrap repetitions. The outcome variables are the inverse hyperbolic sine of public outpatient clinic visits.

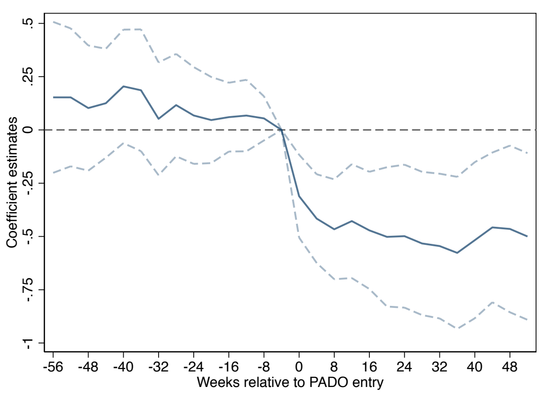
Figure A7:
DiD Estimators Robust to Heterogeneous ATE for SSA ER Visits
for Other Conditions



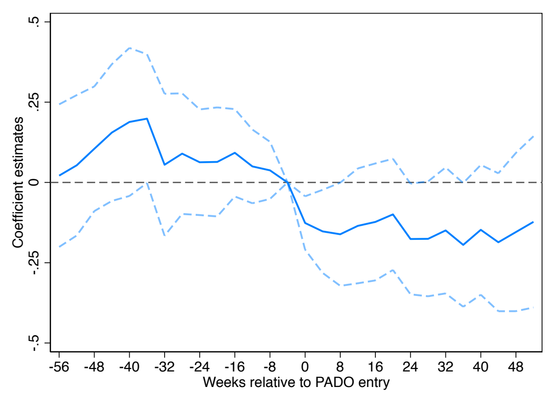
(a) Pneumonia



(b) All diagnoses



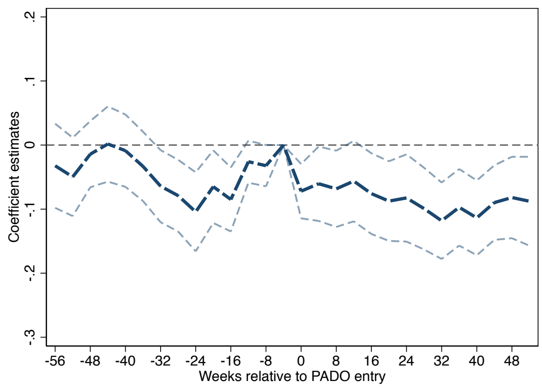
(c) GIDs



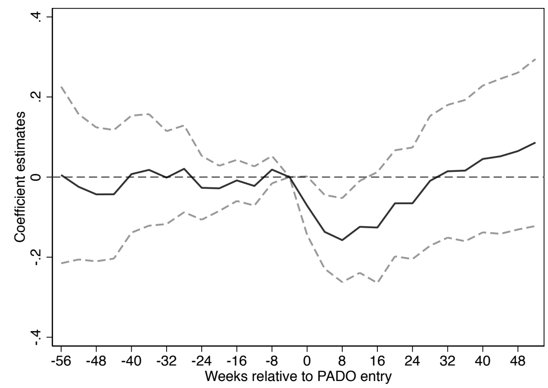
(d) Chronic conditions

Notes: These plots show DiD estimators robust to heterogeneous ATE as described in De Chaisemartin and d'Haultfoeuille (2020) for the effect of PADO entry on SSA ER utilization for conditions different than ARIs. PADOs are matched with SSA ERs within a 5 km radius to construct aggregates of utilization. Each plot considers lead and lag estimates for a two-year window around entry, controlling for PADO and period FE. Dashed lines represent 95% confidence bands constructed from 100 bootstrap repetitions. The outcome variables are the inverse hyperbolic sine of SSA ER visits.

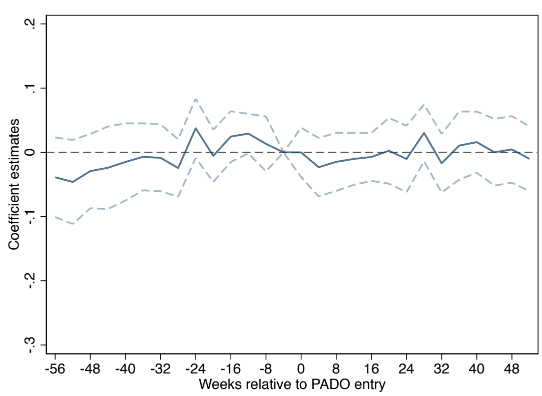
Figure A8:
DiD Estimators Robust to Heterogeneous ATE for SSA Hospital Admissions for Other Conditions



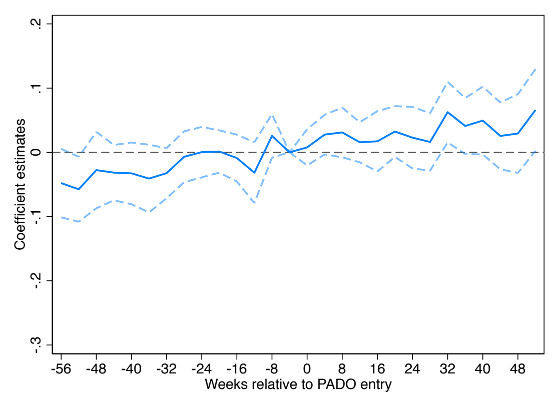
(a) Pneumonia



(b) All diagnoses



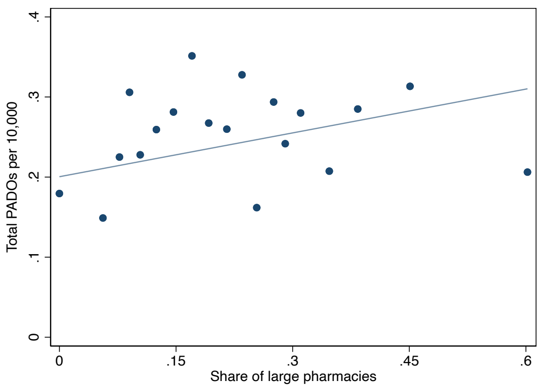
(c) GIDs



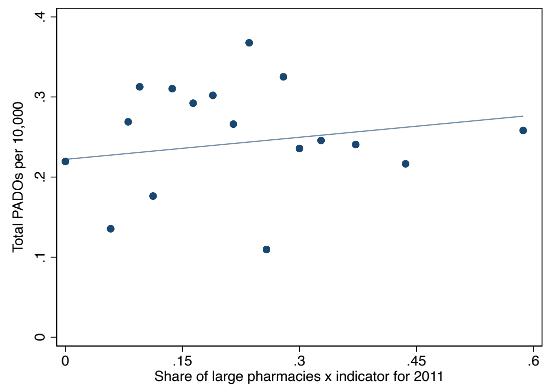
(d) Chronic conditions

Notes: These plots show DiD estimators robust to heterogeneous ATE as described in De Chaisemartin and d'Haultfoeuille (2020) for the effect of PADO entry on SSA hospital admissions for conditions different than ARIs. PADOs are matched with SSA hospitals within a 5 km radius to construct aggregates of utilization. Each plot considers lead and lag estimates for a two-year window around entry, controlling for PADO and period FE. Dashed lines represent 95% confidence bands constructed from 100 bootstrap repetitions. The outcome variables are the inverse hyperbolic sine of SSA hospital admissions.

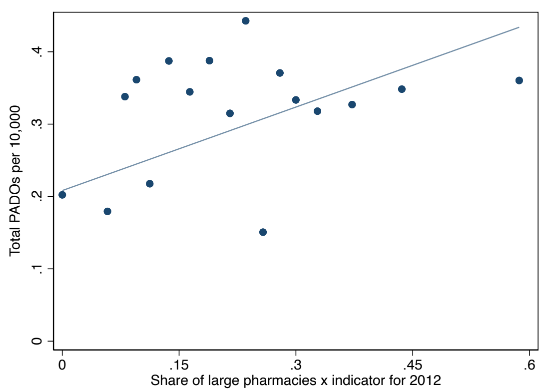
Figure A9:
Correlation between PADOs per Capita and Share of Large Pharmacies



(a) Share of large pharmacies



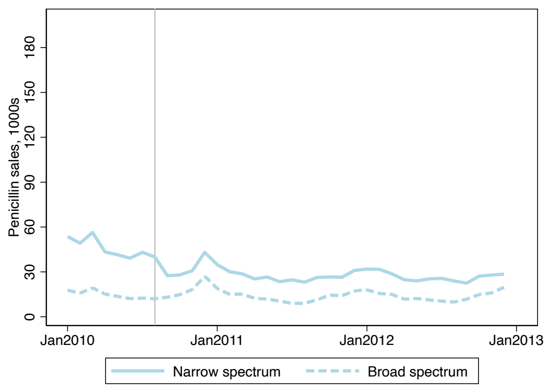
(b) Share of large pharmacies × 2011



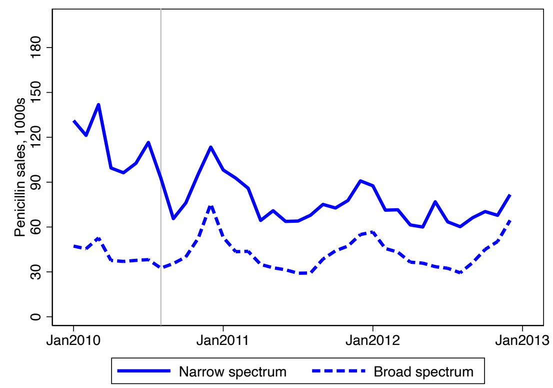
(c) Share of large pharmacies × 2012

Notes: These graphs show evidence of a strong first stage for the IV estimation in the main text. The top left plot shows the correlation between PADOs per 10,000 at the municipality level and the share of pharmacies that are large, defined as retail pharmacy chains that also sell non-pharmaceutical products, according to the 2009 economic census. The top right plot interacts the share of large pharmacies with an indicator for 2011. The graph on the bottom interacts with a 2012 indicator. All binned scatterplots use the number of products in a municipality with positive sales as weights and include the line of best fit.

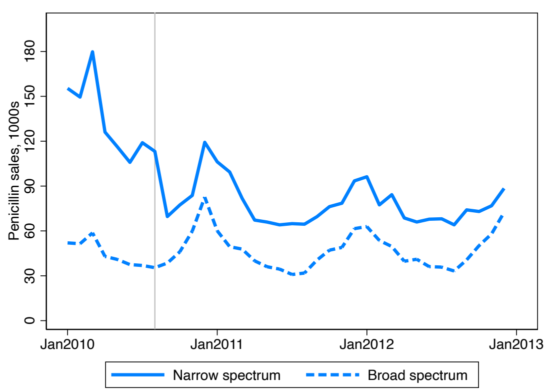
Figure A10:
Time Series of Penicillin Sales



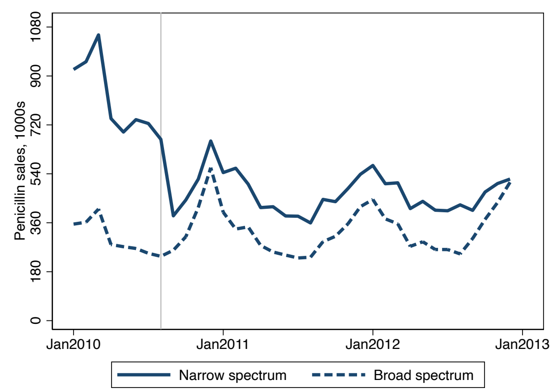
(a) Municipalities with zero PADOs



(b) Municipalities with 1-2 PADOs



(c) Municipalities with 3-5 PADOs



(d) Municipalities with 6+ PADOs

Notes: These plots show the raw time series data for penicillin sales. Each plot corresponds to a different group of municipalities, based on the number of PADOs in December 2012. Each series corresponds to a different type of penicillin. The vertical line signals the law that prohibited over-the-counter sales of antibiotics.

Table A1:
Healthcare Coverage and Primary Healthcare Providers

Healthcare coverage (affiliation)	
Public coverage	73.34%
Public coverage with IMSS	30.41
Public coverage with SSA (SP)	37.57
Private insurance	0.65
No healthcare coverage	25.60
Multiple coverage/affiliations	1.91
Main primary healthcare provider	
Public providers	71.63%
PADOs	10.38
Other 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 healthcare coverage in Mexico, calculated from the 2012 ENSANUT, using survey weights. The first panel shows the percentage of respondents reporting healthcare coverage by type of provider, and the second one shows the percentage reporting each type as their main primary healthcare provider.

Table A2:
Healthcare Utilization 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 shares of actual utilization, calculated from the 2012 ENSANUT, using survey weights and 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	Other 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.

Table A4:
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.

Table A5:
Estimates of PADOs on Probability of Seeking Medical Care and Public Service Characteristics

	Base specification	+ diagnosis controls	+ individual controls	+ differential trends
Panel A: probability of seeking medical care when sick				
Total PADOs per 10,000	-0.044	0.002	0.002	0.005
	(0.037)	(0.008)	(0.008)	(0.008)
Observations	20,900	20,900	20,900	20,900
Mean dependent variable	0.322	0.322	0.322	0.322
Panel B: waiting times at public sector facilities				
Total PADOs per 10,000	-0.766	-0.813	-0.780	-0.586*
	(0.701)	(0.705)	(0.647)	(0.336)
Observations	4,425	4,425	4,425	4,425
Mean dependent variable	75.35	75.35	75.35	75.35
Panel C: duration of consultation at public sector facilities				
Total PADOs per 10,000	0.015	0.048	0.039	0.103
	(0.109)	(0.102)	(0.107)	(0.124)
Observations	4,227	4,227	4,227	4,227
Mean dependent variable	24.82	24.82	24.82	24.82

Notes: This table shows estimates of the association between PADOs per capita and survey responses in the 2006, 2012 and 2018 ENSANUT rounds. Observations are at the individual level for a municipality-year. Panel A considers an indicator for seeking medical care when sick as the outcome. Panel B the inverse hyperbolic sine of waiting times at public facilities. Panel C shows the inverse hyperbolic sine of consultation durations at public facilities. Estimates are shown from regressing each outcome on PADO counts per 10,000, with municipality and year FE. Panels B and C also include public subsystem FE. Regressions include survey weights. Each column adds additional controls. Means of the dependent variables in levels shown. Robust standard errors in parentheses, clustered at the municipality level.
*** p<0.01, ** p<0.05, * p<0.1

Table A6:
Estimates of PADOs on Physician Labor Supply

	Doctors per capita	General doctors per capita	Specialist doctors per capita	Public sector doctors per capita	Public doctors per capita with two jobs
Panel A: baseline specification					
Total PADOs per 10,000	0.163	-0.030	0.318	-0.060	-0.070
	(0.210)	(0.250)	(0.313)	(0.220)	(0.216)
Panel B: differential trend for ever having PADOs					
Total PADOs per 10,000	0.183	-0.020	0.332	-0.051	-0.043
	(0.217)	(0.258)	(0.321)	(0.228)	(0.221)
Observations	17,864	17,864	17,864	17,864	17,864
Mean dep. var.	21.88	16.75	5.139	14.45	3.397

Notes: This table shows estimates of the association between PADOs per capita and physician labor supply at the municipality level, using data from the quarterly employment survey ENOE. Observations are at the municipality-quarter-year level from 2005 to 2015, restricted to municipalities that are continuously observed (i.e., a balanced panel of 406 municipalities). The baseline specification in panel A regresses the inverse hyperbolic sine of the outcome on PADO counts per 10,000, with quarter-year and municipality FE, weighted by the number of individuals with an occupation. Panel B adds a differential linear trend for municipalities that ever have at least one PADO. Each column corresponds to a different measure depending on the type of doctor (general vs specialist), where the doctor works (i.e., public sector), and whether the doctor has more than one job. All doctor measures are in per capita terms (per 10,000 individuals). Means of the dependent variables are also shown. Robust standard errors in parentheses, clustered at the municipality level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A7:
Estimates of PADOs on Healthcare Resources and Visits

	Healthcare units		Healthcare staff		Patient visits	
Total PADOs per 10,000	-0.014	-0.113	-0.027	-0.016	-0.099*	-0.249*
	(0.009)	(0.095)	(0.017)	(0.036)	(0.053)	(0.129)
Observations	108,818	108,818	108,818	108,818	108,818	108,818
R-squared	0.647	0.842	0.668	0.859	0.570	0.659
Weights	None	Units	None	Units	None	Units
Mean dep. var.	1.58	1.58	13.50	13.50	21,812	21,812

Notes: This table shows estimates of the association between PADOs per capita and municipality-level measures of outpatient healthcare resources and patient visits, using data from SIMBAD. Observations are at the municipality-institution-year level for 2,456 municipalities from 2007 to 2014. Outcomes correspond to public outpatient healthcare units, total medical staff per unit, and yearly patient visits per unit. Estimates are shown from regressing the inverse hyperbolic sine of the outcome on PADO counts per 10,000, with year indicators, municipality and institution FE, and a differential linear trend for municipalities that ever have at least one PADO. Every second column weights by the number of public outpatient clinics in 2007. Means of the dependent variables in levels shown. Robust standard errors in parentheses, clustered at the municipality level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$