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, expansions in low-cost private-market healthcare delivery may be welfare-improving by increasing access, but may be sacrificing on quality. I study the introduction of retail clinics at private pharmacies in Mexico. I find that entry led 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 sizable 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

Across settings — such as education, security, waste disposal, and primary healthcare — congested and inefficient public provision often coexists with private market low-cost alternatives.[1] In many developing countries, public provision of healthcare is inefficient (Das et al., 2016; Dizon-Ross et al., 2017), with congestion at facilities decreasing access (Dupas and Miguel, 2017; Ashraf et al., 2014; Christensen et al., 2021).[2] Although private care may be less congested, it is expensive, usually paid out-of-pocket, and may not even be higher quality (Leive and Xu, 2008; Das and Hammer, 2014). Expansions in private-market healthcare delivery, usually in the form of low-cost, limited-service 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 different providers is essential for understanding such markets and informing policy design.

This paper analyzes how entry of a low-cost private provider affects public utilization and explores one channel on which quality may differ at the new facilities. I focus on the expansion of private pharmacy-adjacent doctors' offices (PADOs) — essentially, retail clinics at private pharmacies — in Mexico.[4] Using the PADO registry from the Ministry of Health (SSA), I exploit 5,111 entries, mostly in urban areas, across Mexico from 2005 to 2015.

Accessing anonymized patient records from a medium-sized PADO chain as a case study, I begin by documenting that over half of all PADO visits are for acute respiratory infections

[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 low staffing and absenteeism at facilities (Banerjee and Duflo, 2006).

[3] Other types of expansions may include market-based incentives to channel patients to appropriate medical care and to bolster the diffusion of health information (Björkman Nyqvist et al., 2019; Goldberg et al., 2018). These alternatives are more cost-effective when exploiting existing networks, such as retail pharmacies (Cohen et al., 2015). Similarly, infrastructure networks, such as railroads, may decrease the cost of accessing rural communities (see, for example, the "Tren de la Salud" program in Mexico, https://www.fundaciongrupomexico.org/programas/Paginas/RutasDrVagon.aspx, accessed November 2018).

[4] 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 (e.g., CVS Minute Clinics) are conceptually similar. Therefore, I refer to PADOs as retail clinics.

(ARIs). Thus, I focus the initial analysis on public healthcare utilization for ARIs. With data from public outpatient clinics, emergency rooms (ERs), and hospitals, I construct a balanced panel of ARI visits or hospital admissions at each facility during four-week periods. I then match each PADO entry to public facilities within 5 km and aggregate counts as a measure of public utilization in the local healthcare market around each PADO.

I identify the effect of PADO entry on utilization through an event study design with time period and PADO fixed effects (FE), using the estimators in De Chaisemartin and d'Haultfoeuille (2022) that are robust to heterogeneous average treatment effects (ATE). 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.

I estimate a significant decline in public clinic visits for ARIs of 1-2% after PADO entry, or an average of 13-29 fewer visits per week. For ER visits, I find a large decrease of 64% for ARI visits, or about 15 less per week.[5] Lastly, I do not find significant effects for ARI hospital admissions, though the point estimates suggest one fewer ARI hospitalization every 19 weeks. Overall, these estimates show that PADOs are pulling ARI patients away from public providers at the outpatient level.

Supplementary analyses in the online appendix show that substitution is stronger in markets with more public clinics and with a higher baseline patient volume (i.e., potentially more congested). Moreover, PADOs are associated with a decline in waiting times and a slight increase in the time public clinic doctors spend with patients, consistent with PADOs leading to decongestion of these busy facilities. I find no significant associations between PADOs and ARI death rates nor between PADOs and physician labor supply.

To understand potential spillovers, I analyze other large diagnostic groups. For pneumonia, which acts as a proxy for severe ARIs, I find no significant effects for public clinic visits, although there is a significant impact of around 31% fewer ER visits. For gastrointestinal diseases (GIDs), I find no effects on clinic visits but a strong significant decline at ERs.

[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).

Lastly, I estimate a small but 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 also consistent with decongestion effects at the public clinics.

Altogether, results suggest that PADOs are pulling patients away from ERs for infectious diseases and from outpatient clinics for milder ARIs, which allows more patients with chronic conditions to visit the public clinics. Supplementary analyses show that the decline in ER visits is driven by non-urgent cases. This then seems to suggest that PADOs are welfare-improving for access. However, due to the vertical integration with private pharmacies, there may be additional costs. For instance, the pay structure for PADO doctors suggests strong financial incentives to overprescribe their patients (Díaz-Portillo et al., 2015).

Hence, one potential cost may be related to changes in antibiotic prescriptions. For the 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, and even for patients diagnosed with the common cold, which is most likely caused by a virus. I also report that strong antibiotics are more likely to be prescribed than milder types, conditional on an ARI diagnosis and an antibiotic prescription. For context, less than 5% of common colds are caused by bacteria (see, for instance, Makela et al. 1998). Furthermore, high prescription rates of antibiotics for ARIs is a common problem in other settings: for instance, 27% for Norway in 2003 (Gjelstad et al., 2009), 49% for the US in 2002 (Roumie et al., 2005), and a median of 54% for the UK in 2011 (Gulliford et al., 2014).

To explore the potential consequences on prescribing behavior, I obtain proprietary penicillin sales data from a leading pharmaceutical consulting company. I construct a balanced panel of 183 penicillin products — both narrow and broad spectrum — across 563 municipalities on a monthly basis from 2010 to 2012. Broad spectrum penicillin is stronger, more expensive, and medical guidelines caution against overusing it 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 then analyze the association between PADOs and penicillin sales under a continuous treatment difference-in-differences (DiD), with time, municipality, and product FE, but caution against making a strong causal interpretation due to the pitfalls of these types of designs (Callaway et al., 2021). An instrumental variables (IV) approach complements this analysis, which may provide some support for a causal claim.

The main DiD specification shows that an additional PADO per 10,000 people is associated with a 12% decline in narrow spectrum sales and a 17% increase in broad spectrum sales.[6] This decline in narrow-type sales is concentrated among low-price products, while the increase in broad types is driven by high-price products. Since PADOs are unlikely to treat the more serious ARI cases, and to the extent that stronger penicillin is likely to be medically unnecessary, I interpret this shift toward stronger penicillin types as suggestive evidence that PADOs may sacrifice quality of care due to their direct ties to the pharmacy. However, data limitations — such as not being able to link sales with PADO doctor prescriptions and not observing sales of other types of antibiotics — invite further research.

Overall, this study shows that PADOs may be improving access to healthcare by shuffling non-urgent patients away from congested public ERs, and away from public clinics for milder ARIs. 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

[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).

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.

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 SSA directly in charge of the Seguro Popular subsystem.[7] Healthcare in the public system is free for eligible and enrolled individuals, but it does not cover healthcare costs at private providers. Due to low private insurance rates,[8] most utilization at private facilites is paid out-of-pocket.[9] Further institutional details are provided in the online appendix.

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]

[7]The public system covers 30% of the population at IMSS, and 38% at SSA (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).

Pharmacy-adjacent doctors' offices. Private healthcare is a growing market in Mexico, particularly in the form of 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. Services provided focus mostly on acute infections (Díaz-Portillo et al., 2015).

PADOs are vertically integrated with the private pharmacies and doctors receive a salary from the pharmacy itself, including bonuses. Wages for healthcare professionals are very low and there is vast inequality. In 2012, monthly base salaries at PADOs were on average 5,500 pesos or 458 USD, although monthly income (wages plus additional payments and bonuses) was over 50% higher, at a mean of 8,500 pesos or 708 USD (Díaz-Portillo et al., 2015).[11] This difference stems from financial incentives based on patient volume, prescriptions, or other performance metrics.[12]

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), and many are even free, while healthcare in the public sector is free for those eligible and enrolled, and traditional private providers charge almost seven times as much as PADOs 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

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

[12] A (non-random) sample of online job postings in August 2022 shows variation in these incentives. Some are based on patient volume, medical procedures like injections, or simply "productivity". See the online appendix for more details, including Figure A3.

[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).

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.

PADO entry has concentrated mostly in urban areas. For instance, in the data, I observe PADO entries in 761 municipalities, or around 30% of all municipalities. However, these jurisdictions concentrate about 80% of the total Mexican population. As such, this study is mostly concerned with urban and semi-urban populations where PADOs coexist with other private providers and the public system, and results may not generalize to rural areas characterized by underprovision.

In general, PADO 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 review or 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).

2.1 Conceptual Framework for Provider Choice

A fundamental question is what happens to provider choice when low-cost, limited-service private providers, such as PADOs, enter the market. Suppose a patient derives some value from a particular provider as simply the benefits of care minus the costs. In this setting, the baseline scenario includes both traditional private providers and the public option. Relative to other private clinics, PADOs charge less (lower cost) and may provide more benefits due to convenience (i.e., diagnosis and treatment in a single location) or less benefits due to potentially lower quality. The typical provider-patient agency problem may reduce the saliency or observability of this potential quality issue. Relative to the public option, PADOs charge more (higher cost), but are more convenient and provide quicker service (higher benefits)

[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.

even if quality of care is potentially worse (lower benefits). Ultimately, individual choices will depend on the idiosyncratic value derived from different providers, but, in the aggregate, one would expect that entry leads to some substitution away from existing providers.

A particular question is whether this choice differs by symptom severity so that patients sort along this dimension. If it does not, one would expect substitution patterns that are similar across severity types. But if patients derive a value of care from different providers that is symptom-specific, then we may observe differences in substitution across severity types (e.g., ARIs vs pneumonia or urgent vs non-urgent cases at ERs). If this is the case, then it is key for understanding provider choice, evaluating potential welfare consequences, and designing better regulations.

In addition, PADOs are vertically integrated with the pharmacy. For such a business model of low-price consultations to make sense, the (profit-maximizing) pharmacy's likely strategy is to subsidize the doctor visits while pushing for an increase in prescriptions (or a shift toward more expensive ones) in order to generate more revenue. The small (or even negative) profits in the PADO side of the business can only be sustained with increases in the pharmacy side of the business, both by attracting more patients and increasing pharmacy sales. As in other patient-physician relationships, under asymmetric information, patients may not distinguish between necessary treatments and overprescription, thus exacerbating the PADO doctor's incentives. Taken together, this affects both the cost of care (i.e., the pharmacy subsidizes the doctor visits, resulting in consultations that are very cheap) and the benefits to patients (i.e., doctors have direct financial incentives to overprescribe).

Other retail clinics may not be vertically integrated with a pharmacy. This would affect the value patients derive, potentially by increasing the cost, but also affecting the benefits, which might increase due to not having those direct financial incentives but may also decrease due to the loss in convenience. Furthermore, information asymmetries may lead to other types of financial incentives in these cases. Hence, one might observe different substitution patterns but also different welfare consequences.

Overall, this is ultimately an empirical question since the benefits and costs may vary by type of patient and by local healthcare market. In what follows, I tackle this by analyzing the effect that the entry of PADOs had on public care utilization and by exploring potential changes in prescribing behavior of antibiotics as a proxy for quality of care. The online appendix presents an extension on this simple framework that closely follows Alexander et al. (2019).

2.2 PADO Entry Data

I obtain the full roster of PADOs up to 2019 from the SSA public registry.[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] I do not observe many PADOs exiting the market. Anecdotally, it seems like there has been little exit, and in the data, only 36 PADOs are registered as having exited over this period.

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.

[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 document commissioned by COFEPRIS and prepared by a private consulting company reports 15,000 PADOs in existence in 2014 (see, for instance, the reference in 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 from the National Institute for Access to Public Information and Data Protection or INAI (number 1215100141817), COFEPRIS no longer has this document.

2.3 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 it 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.

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 account for 55% of total visits. The second most common diagnosis, corresponding to GIDs, only makes up about a quarter of this or 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

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

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 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 disclosed 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 obtain geographic coordinates and generate counts by diagnosis at the hospital-by-four-week-period level, eliminating hospitals with zero admissions over more than half the observed periods. The data then consist of 676 hospitals recording about 26.9 million hospitalizations.

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

[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.

Since ERs are generally located at hospitals, 573 of these hospitals correspond to an ER in the previous dataset.

3.2 Empirical Strategy

I 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.

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.

Lastly, 5 km for ERs and hospitals may be too restrictive a catchment area. Indeed, it is likely that even in urban areas, patients must travel larger distances to get to the nearest hospital or ER, relative to outpatient care. Additionally, the relevant substitution may not be around which ER or hospital is within the PADO's catchment area, but rather the ER or hospital corresponding to where the patient lives or where she is eligible for SSA healthcare

[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.

services. Unfortunately, I do not observe where patients live, but as a robustness check, I also present results for ER visits and hospital admissions using larger catchment areas.

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 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.

A recent literature has identified potential issues with the standard staggered-timing two-way fixed effects (TWFE) DiD approach provided in equation 1 due to problematic comparisons between different groups (Goodman-Bacon, 2021; Sun and Abraham, 2020; De Chaisemartin and d'Haultfoeuille, 2020).[25] To address this, I use the estimator presented in De Chaisemartin and d'Haultfoeuille (2022) that is robust to heterogeneous treatment effects and allows for the estimation of dynamic effects. In specifications without control variables (and given that the treatment here is staggered and binary), this estimator is equivalent to the one proposed in Callaway and Sant'Anna (2021).

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.[26] 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 static DiD regression:

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

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.

[25] Goodman-Bacon (2021) shows that the estimator in TWFE regressions is a weighted average of all possible 2×2 DiD. In this setting, it implies that ordinary least squares 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.

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

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 allow for flexible non-parametric time trends at the latitude-longitude grid cell level in equation 1.

Also, 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 using the estimator in De Chaisemartin and d'Haultfoeuille (2022) with one year on either side of entry. Robust standard errors are calculated from 100 bootstrap repetitions.[27] Point estimates are interpreted relative to the four-week period

[27]I perform a block bootstrap a the PADO level by resampling the data randomly. For each repetition, I draw a bootstrap sample, calculate the estimators, and save the results. After 100 repetitions, I use the standard deviation across these estimates to obtain the standard errors.

before the event (the excluded period). All results are shown graphically. Capped spikes represent 95% confidence intervals from robust standard errors clustered at the PADO level. Uncapped spikes show uniform sup-t confidence bands calculated as per Montiel Olea and Plagborg-Møller (2019) and based on an asymptotic variance-covariance matrix clustered by PADO.

Outpatient clinic visits. The top-left graph in Figure 3 shows the effects on public outpatient clinic visits for ARIs. Prior to entry, point estimates are relatively flat and statistically insignificant. There is, however, a hump in the point estimates prior to entry (although these are not significant). After entry, there is a gradual and significant decline in utilization. On average, this effect amounts to a 1% decline in outpatient visits for ARIs and up to 2.3% one year after PADO entry. Given the average number of visits, this implies between 13 and 29 fewer visits for ARIs per week per local market on average.

Figure 4 explores robustness checks under alternative specifications with very similar results. A particular concern is the slight hump in point estimates prior to entry. First, I calculate a linear trend based on all pre-entry coefficients, which I then extend toward the post-entry periods. This allows for a visual inspection of the post-entry results relative to this counterfactual linear trend. Most point estimates are now significant and the magnitude of the decline is larger. Second, I include longitude-latitude cell flexible time trends to account for regional epidemiological trends. Pre-entry coefficients are now very flat and insignificant, with post-entry effects fluctuating at around a 1%, although some estimates are quite noisy. Taken together, these exercises help alleviate concerns with the (insignificant) hump in estimates prior to entry.

The remaining robustness checks in Figure 4 explore alternative ways of aggregating utilization. First, I weight regressions by the number of matched clinics, effectively up-weighting larger markets (i.e., those that are served by more public clinics). Second, I use inverse-distance weighted aggregates of ARI visits, so that nearby clinics contribute more to the measure of ARI visits in the local market. Third, I include always-treated and never-treated units (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. In all cases, results are quite similar.

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.

Furthermore, using information on the average entry rank for the matched clinics for each PADO, online appendix Figure A5 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 or consumer learning.

Finally, and for completeness, Table 2 presents DiD estimates from equation 2. Panel A zooms in on a one-year window on either side of entry (with smaller windows for entries in the first and last year of the sample period due to data availability). Panel B uses the full dataset. The first seven columns in Table 2 show different specifications for outpatient visits, based on the robustness checks from above. Estimates range from a 0.6 to 1.5% decline in ARI visits after PADO entry. Most estimates are statistically significant in Panel A, but are more noisily estimated in Panel B. Lastly, Columns 2 and 3 also partition the sample based on PADO entries before and after 2010, when the antibiotics prescriptions law was passed. A test does not reject that the effect sizes are statistically the same in both periods.

SSA ER visits. The top-right graph in Figure 3 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 64% decline in ER visits for ARIs after PADO entry. This amounts to a little over 15 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.

Supplementary analyses in appendix Figure A6 show that the share of non-urgent (as classified by the ER physician) ARI visits declines by around 10 percentage points or around 27% of the mean fraction of non-urgent visits. This suggests that PADOs are capturing less severe ARI cases that would have wound up at the ER in the absence of a PADO.

SSA hospital admissions. The bottom graph in Figure 3 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 somewhat lower levels of ARI admissions, most of which are insignificant. Regardless of significance, on average, the estimates correspond to an 7.7% decline in hospitalizations after entry. This amounts to about one fewer ARI hospitalization every 19 weeks. The analogous DiD results in the last column of Table 2 are also weak: 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.

Given the low levels of private insurance coverage (see Section 2), a large percentage of inpatient care occurs in the public sector. In essence, the public system is the final insurer for hospitalizations. Hence, not observing any increases in admissions suggests that health is not adversely affected after PADO entry, at least in terms of severe outcomes that would necessitate inpatient care.

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 weak evidence of a small 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.

Given that PADOs are mostly an urban phenomenon, auxiliary analyses in the online appendix explore heterogeneous effects along this dimension. Figure A7 shows slightly larger effects when restricting to one randomly chosen PADO event per municipality. Figure A8 shows that the decline in outpatient visits is concentrated in local markets that have more public clinics (i.e., there is low substitution in the more isolated markets). However, Panel A in Table A5 shows that stratifying PADO entries by the urbanicity of the municipality does not yield statistically different effects between the more and less urban areas.

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 A6 suggest that PADOs are associated with a large decline in waiting times at public clinics. 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 A7. 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.[28]

To complement this, 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 A8 shows insignificant negative associations between PADO presence and both healthcare units and staffing. For the latter, point estimates are below 3%. This effect would imply on average 0.03 fewer medical personnel. In contrast, these data do show a significant decline in total patient visits. This exercise confirms the notion that public healthcare resources are mostly fixed during the study period.

Beyond hospital admissions, I also estimate the effect of PADO entry on in-hospital deaths in Figure A9, finding no significant impacts. Additionally, I explore the association between municipality ARI death rates and total PADOs per capita in Table A9 using vital statistics data. I find small and insignificant coefficients, suggesting a null association. This may suggest that PADO quality for ARIs is not leading to increases in death rates.

Lastly, there is a question about external validity since the PADO expansion is mostly urban. Substitution patterns may differ if rural public clinics are less congested or if staffing and adequate medical supplies are more of an issue. Likewise, the healthcare choice for patients may be different in more isolated areas due to transportation costs, and there is the question of whether PADOs would be able to locate in local markets that are underserved by the public sector. However, given that PADOs have expanded in areas with high potential demand, the estimates above are policy relevant, even if not generalizable to rural areas.

Robustness checks. Additional results are shown in the online appendix. For completeness, Figure A10 shows standard TWFE event studies, with very similar results. Figure A11

[28] 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 A7 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).

shows robustness of the ER and hospital admissions results to constructing larger catchment areas. Lastly, Figure A12 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.

Pneumonia. The top-left plot in Figure 5 shows the results for pneumonia outpatient visits (data are only available from 2007 to 2014). Most estimates are statistically indistinguishable from zero although perhaps there are slightly lower levels for the post-entry periods. If pneumonia is a proxy for severe ARIs, this may suggest that ARIs seen at PADOs are less severe on average. The top-right graph in Figure 5 shows a significant decline in SSA ER visits for pneumonia following PADO entry. The average impact is around 31% fewer ER visits. Lastly, the bottom graph shows mostly no effects on pneumonia hospitalizations given the pre-entry levels.

GIDs. The top-left 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 next graph shows a significant decline in SSA ER visits for GIDs after PADO entry, with an average effect of 48%. Lastly, the bottom graph shows essentially a null impact on GID hospitalizations.

Chronic conditions. Figure 7 shows the estimates for chronic conditions. The top-left graph depicts coefficients for visits at public outpatient clinics. Estimates are zero and insignificant prior to entry, but there is a significant increase of around 1% post-entry. Note that this effect only appears until after almost a year post-entry, and there is evidence of a slight drop in visits in the first few weeks. The top-right graph in Figure 7 shows a decline in SSA ER visits for chronic conditions after PADO entry, although estimates are not significant. Lastly, the bottom plot suggests perhaps a small increase in chronic disease admissions at SSA hospitals, though point estimates are generally insignificant at conventional levels.

All conditions. The estimates in Figure 8 largely echo the ARI results. There is a significant decline in total outpatient visits (top-left graph) and a large and significant decrease in SSA ER visits (top-right graph). Lastly, I estimate a bit of a dip in total hospital admissions in the early weeks post-entry that later reverts to pre-entry levels (bottom graph).

Discussion. Although there are no significant impacts on outpatient clinic visits for GIDs and pneumonia, 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. This is consistent with the evidence that the share of non-urgent ER visits for all diagnoses decreases after entry (online appendix Figure A6).

Furthermore, I estimate somewhat of an increase in outpatient visits for chronic conditions, with perhaps slight declines in ER visits. This raises the possibility of a positive spillover that may allow patients to better monitor their chronic diseases at public clinics after PADO entry, although there are no declines in hospital admissions, which is a common marker of better chronic disease management. Nevertheless, the associations with waiting times at public clinics (appendix Table A6) do suggest that PADOs may be increasing access for chronic disease patients by pulling mild infectious cases away from these clinics.

I again explore effects on in-hospital death counts and death rates in Figure A9, finding no significant impacts across diagnoses. Given that the majority of hospitalizations occur in the public system, this is reassuring in suggesting that PADO entry is not associated with extremely adverse health effects. I complement this with estimates in Table A9, showing a null relationship between pneumonia death rates and total PADOs per capita. Taken together, these results suggest that PADO quality is not leading to an increase in mortality.

Robustness checks. Standard TWFE event studies with similar results are shown in online appendix Figures A13, A14, and A15.

5 Potential Costs in Prescribing Behavior

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 because of lax regulations and misaligned financial incentives due to PADO doctors being pharmacy employees and due to the vertical integration with the pharmacies. This section explores one possible cost in the form of changes in the types of antibiotics prescribed, which I broadly associate with quality. The goal is not to provide an exhaustive analysis of potential downsides of PADOs, but to illustrate one particular trade-off of the positive impacts on access.

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 estimate 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, shifted by the sample mean and with 95% confidence intervals, are shown in the top right plot of Figure 2. Even after accounting for physician-specific practices and 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 consistently high, with an over 50% chance 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.[29] This information is compiled by Knobloch Group (KG), the leading pharmaceutical marketing data firm in Mexico.[30] The data records the product name (at the SKU level), dosage-units sold,[31] and total revenue at the city level. I calculate average prices dividing revenue by units sold, and impute product-month-year-specific aver-

[29] Public-sector pharmacies 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 (ENSANUT 2012).

[30] 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.

[31] 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.[32] Matching publicly available records from COFEPRIS, I assign the chemical composition and manufacturer to each penicillin product.[33] 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

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.[34]

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,

[32]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.

[33]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.

[34]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 q_{amt} is the 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 narrow spectrum penicillin, $\mathbb{1}_{[a=\text{broad}]}$ indicates broad spectrum, 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 by municipality.

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.

However, in an attempt to provide some support for a causal effect, I also present an IV estimation. I generate municipality-month aggregates 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.

For the IV strategy, 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. Large pharmacies are defined in the economic census as retail chains that also sell non-pharmaceutical products, similar to CVS in the US. Municipalities with a larger share of these types of pharmacies tend to see more PADO expansion, perhaps because these firms are better able to shoulder the fixed costs of setting up a PADO. In addition to presenting the first stage estimates below, online appendix Figure A16 also inspects this relationship 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. I argue that the exclusion restriction is likely to hold since I observe these pharmacy shares in 2009, a full year before the sales data begin, which precludes endogenous firm expansion from biasing the estimates.

5.4 Results

Table 4 presents the results. The first five columns show coefficients from estimating equation 3. The baseline finding 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 reported in appendix Table A10, I do not find evidence of a significant change in total penicillin units sold (although it should be noted that the data only record penicillin and not all types of antibiotics).

Results are similar across alternative specifications. 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.

The last three 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 base specification here 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 two columns show the IV strategy. The first stage is shown in the next-to-last column. There is a significant and positive association between total PADOs per 10,000 and the share of large pharmacies in 2009 interacted with yearly indicators. The last column shows the 2SLS estimate, which is an order of magnitude larger than the OLS estimate and statistically significant. Since IV recovers a local ATE (for compliers), this coefficient may not be comparable to the OLS effect.[35] Recovering the full ATE would require knowing the effects for non-complier municipalities. As such, not only is the IV estimate conceptually different from OLS, but it may also not be the policy-relevant estimator. Overall, I simply interpret the IV exercise as confirmation that PADOs are associated with a shift towards stronger antibiotic prescriptions. As for the magnitude, the OLS estimate may be more informative of the average, policy-relevant effect of PADO expansion.

Discussion. 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 and a smaller share of narrow spectrum products. Given the price differences (Table 3), this compositional shift is consistent with financial incentives of vertically integrated pharmacies that may be trying to oversell their patients. Auxiliary results in online appendix Figure A17 indicate that the decline in narrow spectrum penicillin is concentrated in products that have a low price (below the median) among these types of antibiotics, while the increase in broad spectrum is driven by products with a high price, consistent with the financial incentive to oversell. To the extent that stronger penicillin may be medically unnecessary and could contribute to antibiotic resistance, I interpret these results as suggesting that PADOs offer lower quality of care on this dimension.

[35] In this setting, compliers would be municipalities that increased the number of PADOs during this period if they had a bigger share of large pharmacies, and did not see an expansion in PADOs if they had a smaller share of large pharmacies. In contrast, one may consider municipalities that would see PADO expansion regardless of the number of large pharmacies (always-takers) or municipalities that would not have more PADOs no matter the share of large pharmacies (never-takers).

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 5) 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 only driven by the 2010 law prohibiting over-the-counter sales of antibiotics. Online appendix Table A11 shows that the estimated associations hold in the post-law period (starting in January 2011), by the time the potentially confounding effects of the regulation would have stabilized. Comparing effects before and after this law, a test does not allow me to reject similar declines in narrow spectrum penicillin with PADO expansion in this time period, although the increment in broad spectrum penicillin is only present after 2010. This may suggest that financial incentives for PADOs became more salient once prescribers became gate-keepers for antibiotics, although data constraints (only penicillin products from 2010 to 2012) do not allow for a more definitive conclusion.

Furthermore, I cannot directly link the data with prescriptions made by PADO doctors. Thus, other types of patient selection or changes in the supply of traditional private providers associated with PADO entry may also explain these results. Moreover, I cannot observe dispensing at public pharmacies, which may also confound the estimates. I also do not observe other therapeutic classes of antibiotics, which does not allow me to say anything about *total antibiotic* prescriptions. Hence, the reader must exercise caution when interpreting this as definitive evidence on the quality of care at PADOs.

Notwithstanding these limitations, the results do seem to suggest the possibility of additional costs associated with the proliferation of retail clinics (namely, PADOs overselling patients), particularly in a setting where PADOs have strong financial incentives, regulations are lax, and patients are being pulled away from public clinics, where these financial incentives are nonexistent. Enforceable regulations such as auditing prescriptions and requiring more transparency in how doctors are paid may help curb these unintended behaviors stemming from this vertical integration.

6 Conclusion

As low-cost, 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 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 types of low-cost providers expand.

From a policy perspective, these results inform the need for stronger regulations, such as monitoring prescription practices and increasing transparency of these types of behaviors, particularly when retail clinics are vertically integrated with pharmacies. 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 other contexts where private and public provision coexist.

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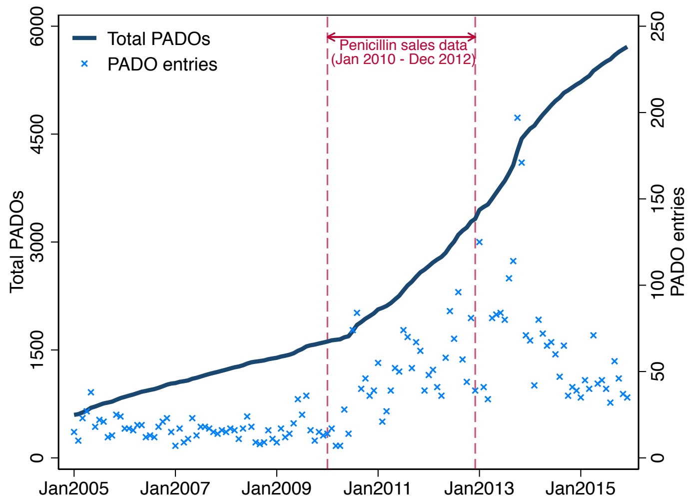
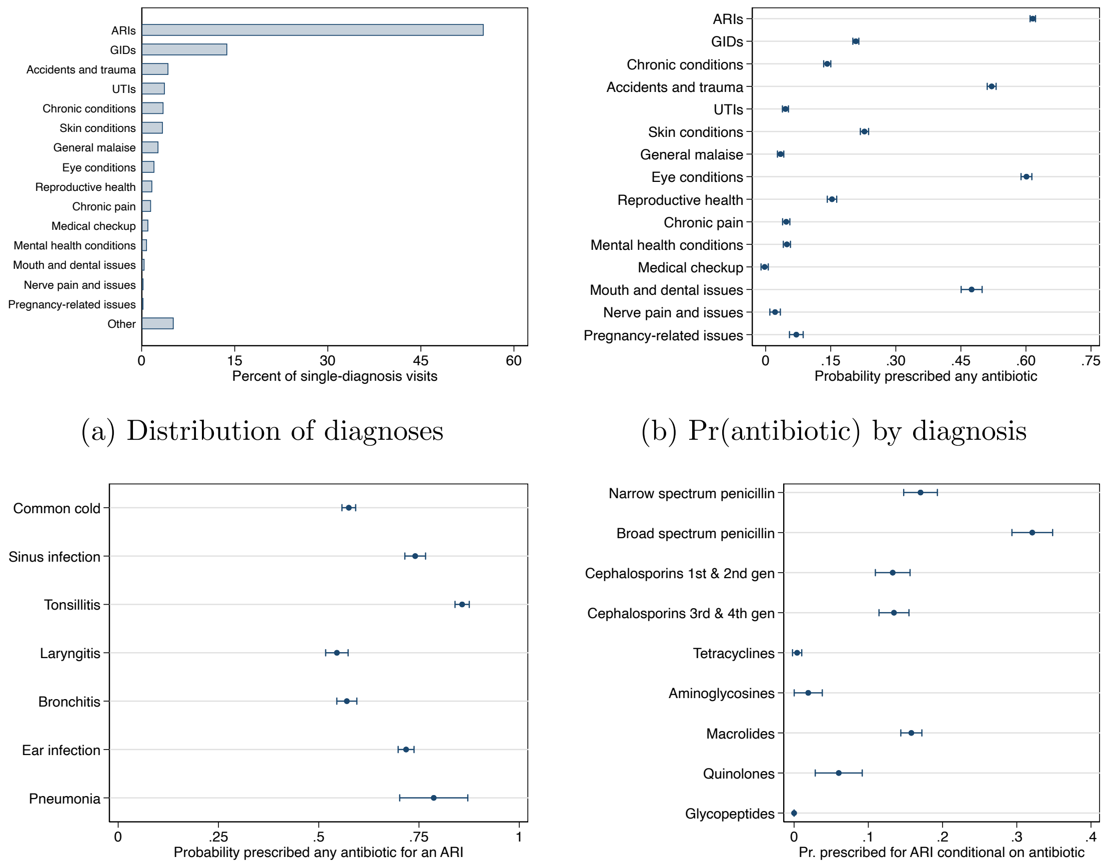
Figures and Tables

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

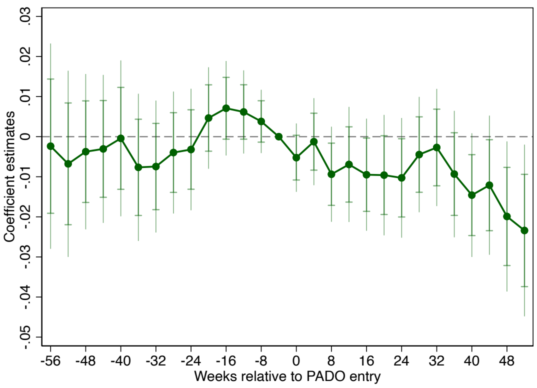
(b) Pr(antibiotic) by diagnosis

(c) Pr(antibiotic) by ARI diagnosis

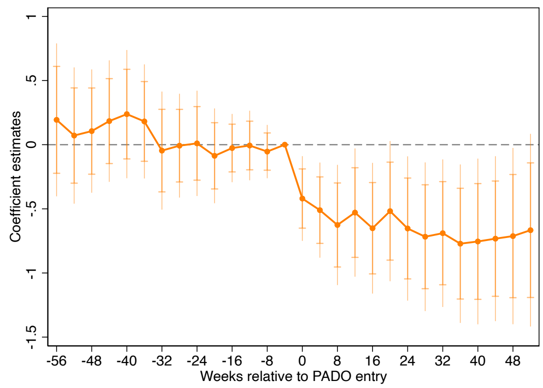
(d) Types of antibiotics for ARI diagnoses

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.

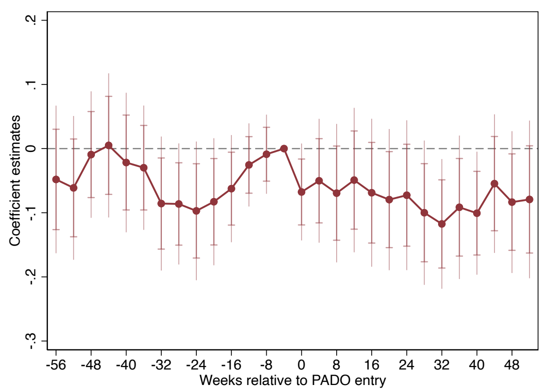
Figure 3:
Utilization of Public Healthcare Services for ARIs and PADO Entry



(a) Public outpatient clinics



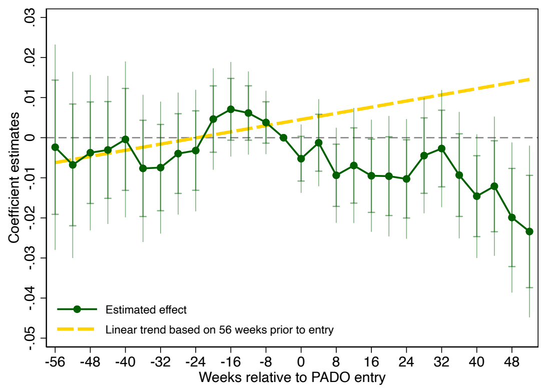
(b) SSA Emergency Rooms



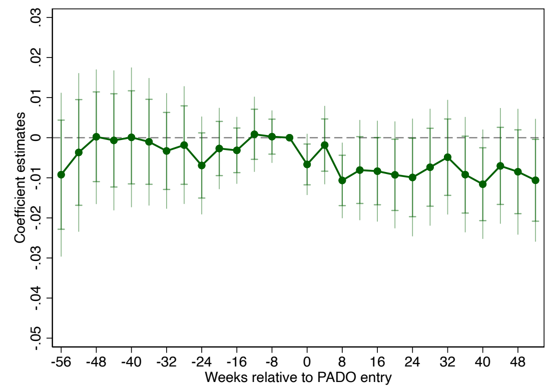
(c) SSA hospitals

Notes: These plots show event studies of PADO entry on public healthcare utilization for ARIs. The first graph considers all public outpatient clinics (5,111 events from 2005 to 2015), the second plot shows SSA emergency room visits (157 events from 2008 to 2015), and the last graph is for SSA hospital admissions (444 events from 2005 to 2015). Each PADO is matched with public healthcare facilities within a 5 km radius to construct aggregates of utilization. Each graph shows the coefficients from regressing the inverse hyperbolic sine of visits or admissions on a vector of leads and lags of PADO entry, with PADO and time period FE, using DiD estimators robust to heterogeneous ATE (see text for details). Capped spikes represent 95% confidence bands constructed from 100 bootstrap repetitions with robust standard errors clustered at the PADO level, while uncapped spikes show uniform confidence bands (see text for details).

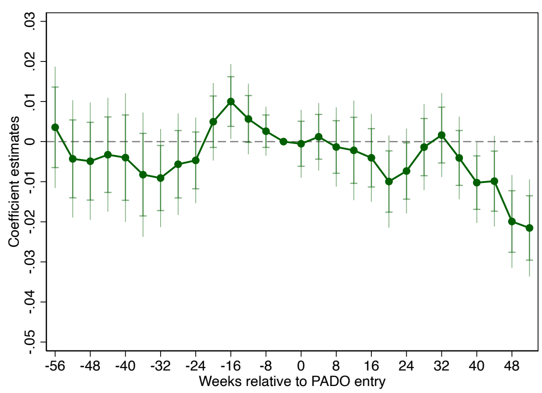
Figure 4:
Alternative Specifications for Utilization of Public Outpatient Services for ARIs and PADO Entry



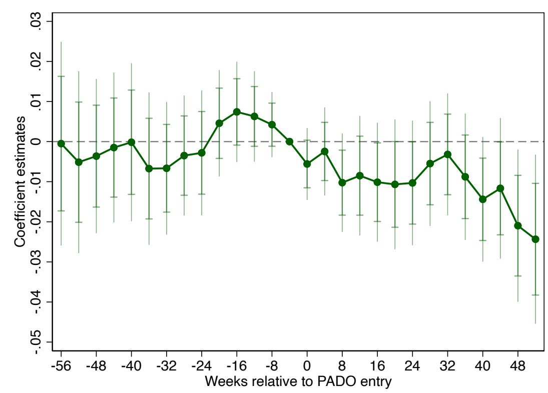
(a) Linear trend



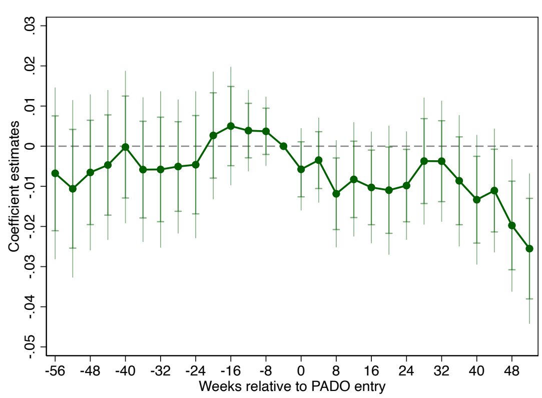
(b) Latitude-longitude cell trends



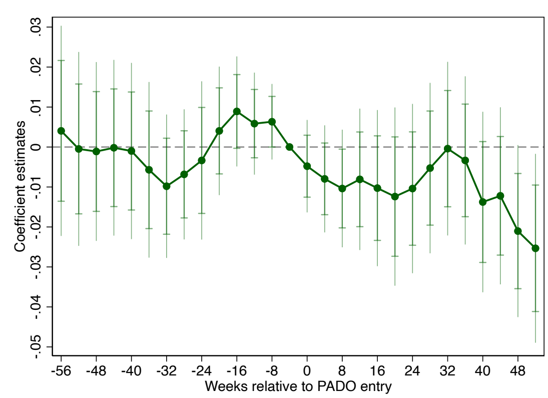
(c) Weighted by market size



(d) Inverse-distance weighted aggregates



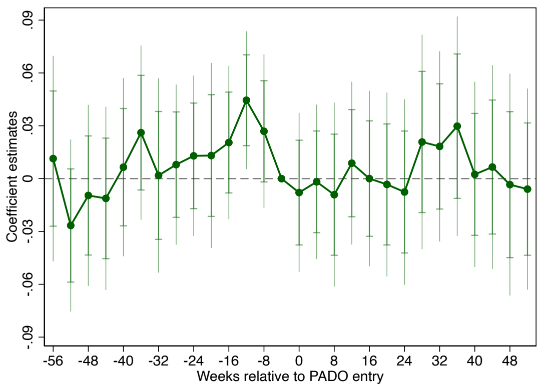
(e) Including all PADO entries



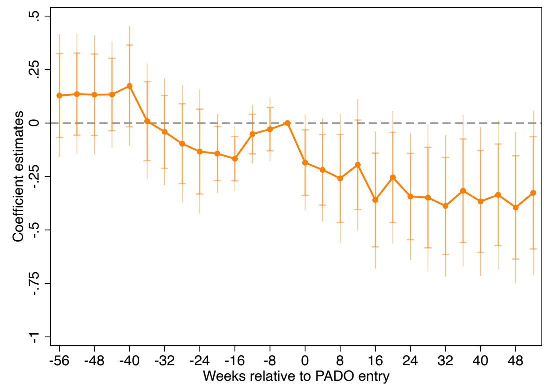
(f) Aggregates within 2.5 km of PADO

Notes: These plots show alternative specifications for the event studies of PADO entry on public outpatient utilization for ARIs (see text for details). Each PADO is matched with public healthcare facilities within a 5 km radius to construct aggregates of utilization. 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, using DiD estimators robust to heterogeneous ATE (see text for details). Capped spikes represent 95% confidence bands constructed from 100 bootstrap repetitions with robust standard errors clustered at the PADO level, while uncapped spikes show uniform confidence bands (see text for details).

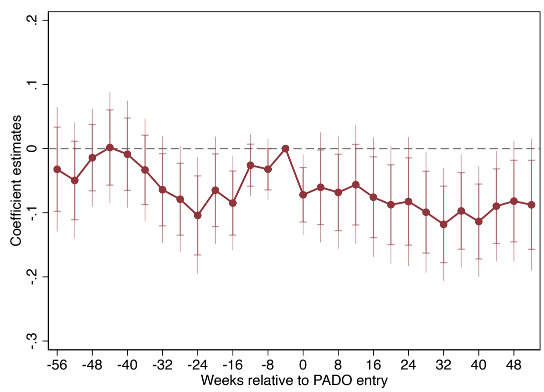
Figure 5:
Utilization of Public Healthcare Services for Pneumonia and
PADO Entry



(a) Public outpatient clinics



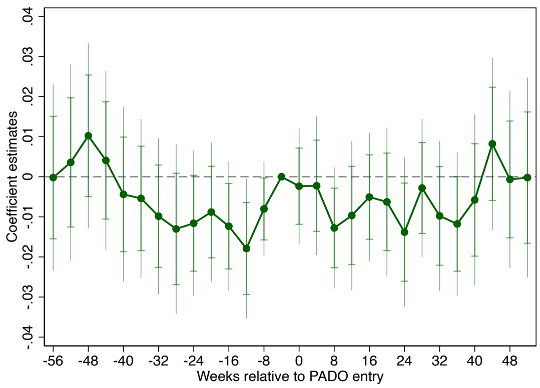
(b) SSA Emergency Rooms



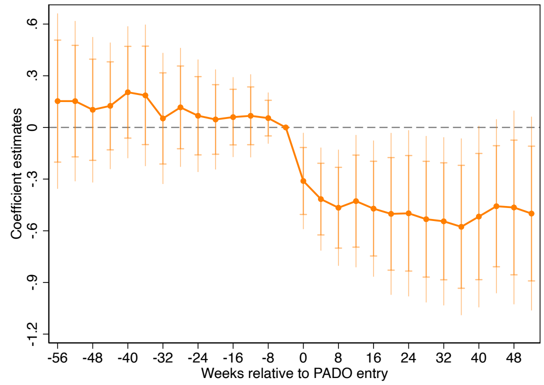
(c) SSA hospitals

Notes: These plots show event studies of PADO entry on public healthcare utilization for pneumonia. The first graph considers all public outpatient clinics (4,140 events from 2007 to 2014), the second plot shows SSA emergency room visits (157 events from 2008 to 2015), and the last graph is for SSA hospital admissions (444 events from 2005 to 2015). Each PADO is matched with public healthcare facilities within a 5 km radius to construct aggregates of utilization. Each graph shows the coefficients from regressing the inverse hyperbolic sine of visits or admissions on a vector of leads and lags of PADO entry, with PADO and time period FE, using DiD estimators robust to heterogeneous ATE (see text for details). Capped spikes represent 95% confidence bands constructed from 100 bootstrap repetitions with robust standard errors clustered at the PADO level, while uncapped spikes show uniform confidence bands (see text for details).

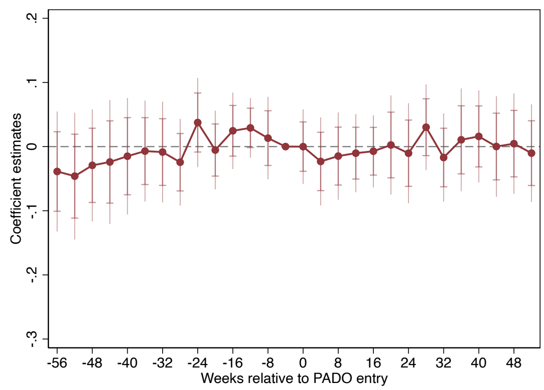
Figure 6:
Utilization of Public Healthcare Services for GIDs and PADO Entry



(a) Public outpatient clinics



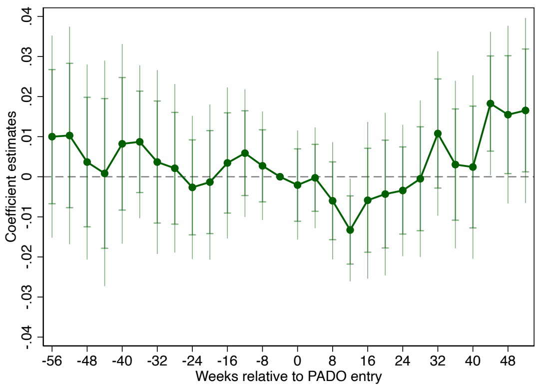
(b) SSA Emergency Rooms



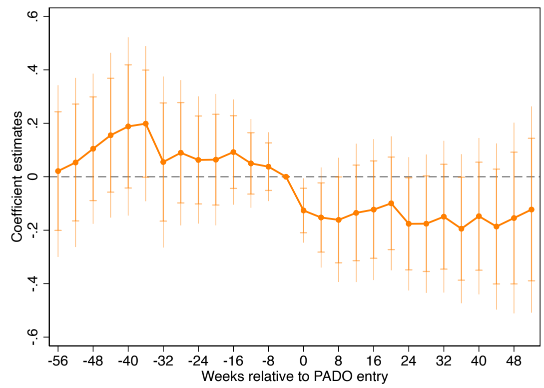
(c) SSA hospitals

Notes: These plots show event studies of PADO entry on public healthcare utilization for GIDs. The first graph considers all public outpatient clinics (5,111 events from 2005 to 2015), the second plot shows SSA emergency room visits (157 events from 2008 to 2015), and the last graph is for SSA hospital admissions (444 events from 2005 to 2015). Each PADO is matched with public healthcare facilities within a 5 km radius to construct aggregates of utilization. Each graph shows the coefficients from regressing the inverse hyperbolic sine of visits or admissions on a vector of leads and lags of PADO entry, with PADO and time period FE, using DiD estimators robust to heterogeneous ATE (see text for details). Capped spikes represent 95% confidence bands constructed from 100 bootstrap repetitions with robust standard errors clustered at the PADO level, while uncapped spikes show uniform confidence bands (see text for details).

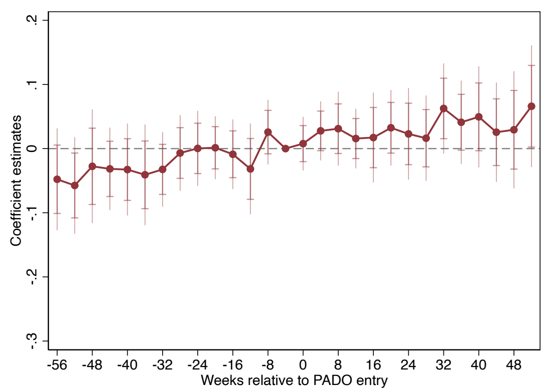
Figure 7:
Utilization of Public Healthcare Services for Chronic Conditions
and PADO Entry



(a) Public outpatient clinics



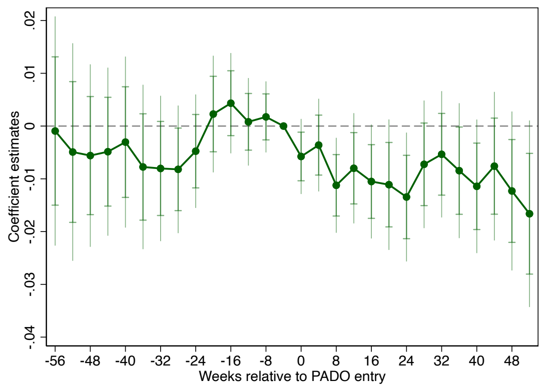
(b) SSA Emergency Rooms



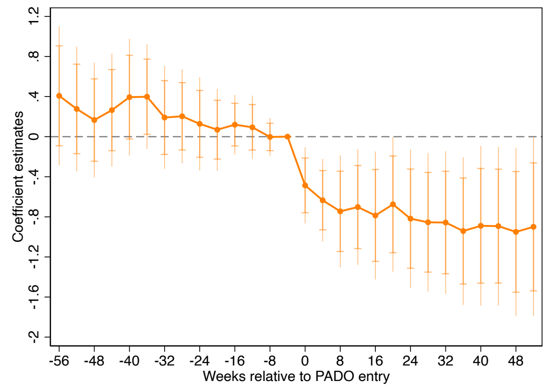
(c) SSA hospitals

Notes: These plots show event studies of PADO entry on public healthcare utilization for chronic conditions. The first graph considers all public outpatient clinics (5,111 events from 2005 to 2015), the second plot shows SSA emergency room visits (157 events from 2008 to 2015), and the last graph is for SSA hospital admissions (444 events from 2005 to 2015). Each PADO is matched with public healthcare facilities within a 5 km radius to construct aggregates of utilization. Each graph shows the coefficients from regressing the inverse hyperbolic sine of visits or admissions on a vector of leads and lags of PADO entry, with PADO and time period FE, using DiD estimators robust to heterogeneous ATE (see text for details). Capped spikes represent 95% confidence bands constructed from 100 bootstrap repetitions with robust standard errors clustered at the PADO level, while uncapped spikes show uniform confidence bands (see text for details).

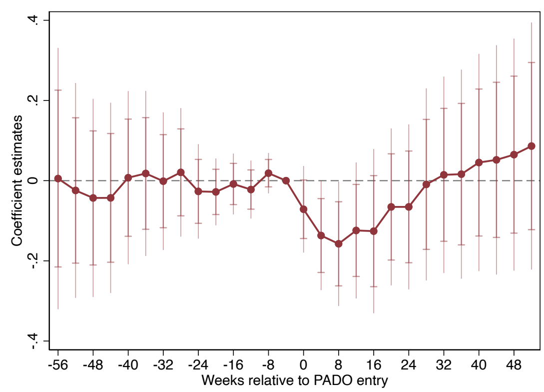
Figure 8:
Utilization of Public Healthcare Services for All Diagnoses and
PADO Entry



(a) Public outpatient clinics



(b) SSA Emergency Rooms



(c) SSA hospitals

Notes: These plots show event studies of PADO entry on public healthcare utilization for all diagnoses. The first graph considers all public outpatient clinics (5,111 events from 2005 to 2015), the second plot shows SSA emergency room visits (157 events from 2008 to 2015), and the last graph is for SSA hospital admissions (444 events from 2005 to 2015). Each PADO is matched with public healthcare facilities within a 5 km radius to construct aggregates of utilization. Each graph shows the coefficients from regressing the inverse hyperbolic sine of visits or admissions on a vector of leads and lags of PADO entry, with PADO and time period FE, using DiD estimators robust to heterogeneous ATE (see text for details). Capped spikes represent 95% confidence bands constructed from 100 bootstrap repetitions with robust standard errors clustered at the PADO level, while uncapped spikes show uniform confidence bands (see text for details).

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.	PADO events until 2010	PADO events post-2010	Incl. PADO events post-2015	Incl. lat.-lon. grid cell trend	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**	-0.0060	-0.0126**	-0.0098**	-0.0067*	-0.0116***	-0.0110*	-0.7022***	-0.0023
	(0.0044)	(0.0070)	(0.0060)	(0.0044)	(0.0039)	(0.0045)	(0.0062)	(0.2109)	(0.0294)
Observations	438,552	126,512	312,040	460,964	438,551	438,552	420,111	12,689	38,312
R-squared	0.9555	0.9576	0.9547	0.9564	0.9660	0.9538	0.9286	0.5473	0.6735
Mean dep. var.	4,940	4,705	5,036	4,998	4,940	5,107	1,868	106.3	1.93
Panel B: full sample									
After entry	-0.0115	-0.0086	-0.0077	-0.0112	-0.0093	-0.0129*	-0.0150*	-0.5128**	-0.0918*
	(0.0074)	(0.0135)	(0.0104)	(0.0069)	(0.0058)	(0.0075)	(0.0090)	(0.2541)	(0.0484)
Observations	730,873	203,203	527,670	822,965	730,873	730,873	700,414	16,328	63,492
R-squared	0.9374	0.9270	0.9412	0.9379	0.9565	0.9355	0.9040	0.5154	0.6155
Mean dep. var.	4,811	4,574	4,902	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 seven columns), SSA ERs (eighth 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 next two columns split by PADO events occurring pre- and post-2010. The fourth column includes PADO events occurring after 2015. Column 5 adds latitude-longitude grid cell flexible trend controls. Column 6 uses inverse-distance weighted aggregates of the matched clinics. Column 7 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.	First stage	2SLS
Total PADOs per 10,000	-0.129**	-0.153***	-0.129**	-0.126**	-0.129**			
× narrow spectrum	(0.061)	(0.059)	(0.059)	(0.059)	(0.059)			
Total PADOs per 10,000	0.188***	0.137**	0.193***	0.205***	0.193***			
× broad spectrum	(0.058)	(0.057)	(0.048)	(0.048)	(0.048)			
Total PADOs per 10,000						0.035**		0.269***
						(0.015)		(0.102)
Share large pharmacies							0.058***	
× 2011							(0.022)	
Share large pharmacies							0.170***	
× 2012							(0.038)	
Observations	1,381,464	1,381,140	1,381,464	1,333,116	1,106,064	20,160	20,160	20,160
R-squared	0.541	0.580	0.797	0.793	0.802	0.724	0.910	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	0.204
Mean PADOs	3.83	3.83	3.83	3.62	5.32	3.83	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 three 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 (OLS) includes municipality and time period FE, and the last two columns show the IV approach 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. Patients do not pay fees for doctor visits or hospitalizations as long as they are currently eligible for healthcare services at that particular subsystem (i.e., as long as they are enrolled). There is generally very low portability of benefits from one public system to the other, and benefit plans (i.e., types of services provided) 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 More Details on Payment Schemes for Doctors at PADOs

Anecdotally, it is well known that PADOs incentivize doctors to increase their patient volume and/or the pharmacy sales through prescriptions. However, there is little robust evidence on this.

Surveying the literature, only Díaz-Portillo et al. (2015) has documented doctor compensation at PADOs. This study surveyed medical personnel at PADOs and other traditional private clinics in 2012 across 18 of the 32 states in Mexico. Although their sample size is small (N=239 physicians, 80 of which work at PADOs), this is the only systematic information on wages and payment schemes. The key result is that doctors report a monthly income from working at the PADO that is on average 54% larger than what they report as their wage. However, direct questions on whether the PADO compensates them for prescribing medications or patient volume show very small percentages (4% and 12.5%, respectively). Nevertheless, the mismatch between total income and wage suggests additional financial compensation. Note also that among doctors at other private providers, the average monthly income is only 1.7% larger than the average wage. Once again, this suggests an important difference in how PADOs pay their doctors.

To try to provide more information on this, I show three examples of job postings for doctors at PADOs on the commonly used website OCC. Figure A3 contains the original ads. These ads were taken between August 29 and September 2, 2022. However, they seem to be in line with the evidence of how doctors have been paid at PADOs since their inception. These examples show that doctors indeed get more money for patient volume and for "productivity" bonuses. The ads also mention additional types of bonuses. Given the public nature of the ads, it is unlikely that one would find an explicit statement for the financial incentive of overprescribing or directly tying pharmacy sales to the doctor.

However, these ads do suggest that there are strong financial ties between the operation of the PADO and how doctors are paid.

C More Details on Conceptual Framework

This section provides more details related to the conceptual framework in the main text and relies heavily on Alexander et al. (2019).

Patients in a given health market face a set of available providers from which they can choose. In this particular setting, one may think of three types of providers: PADOs, other private providers, and public clinics. For each, there is a value that patients derive from obtaining care, which amounts to all the benefits (i.e., getting better, quality of care, amenities that patients may care about, etc.) minus the costs of seeking care at this provider (time, money, etc.). This value may be positive or negative, and I assume that the value of the outside option of not seeking professional care (i.e., self-medicating) is normalized to zero.

An important consideration is how this value varies by symptoms, or more specifically, by ARI severity. Hence, one can think of a value function for each provider that depends on symptom severity. As in Alexander et al. (2019), I assume that all costs and benefits are bounded and that the value derived from any provider is weakly increasing in severity. Note, however, that this second assumption may not necessarily hold: perhaps for severe cases, choosing a PADO may delay necessary inpatient care, resulting in a lower value than less severe cases. However, this may require a more complex framework that considers a dynamic approach to provider choice.

The strongest assumptions, though, relate to the relative values derived from each type of provider. Note that the perceived benefits of care at any provider also depend on how observable quality is for the patient. Under asymmetric information (as is usually the case given the provider-patient agency problem), patients may not be able to fully observe the quality of care provided. Based on the setting and additional information discussed in the text, I start with the following assumptions, though many other scenarios could be conceived:

- Mild cases: PADOs provide the most value (since they are cheap and convenient and care is fairly standard for these cases), followed by private providers (since on average they are more expensive while not really providing many more benefits when ARIs are mild), and lastly public clinics (mainly, because waiting times are very high).

- Medium-severity cases: since these cases may require more expertise, potentially higher quality doctors at other private providers may yield the largest value, followed by PADOs (whose doctors may have less experience), and lastly public clinics (again, due to large costs related to congestion, and because the risk of requiring inpatient care in not that high).

- Severe ARIs: public clinics provide the most value (because there is a larger risk of being hospitalized and most patients cannot pay for private inpatient care, which is consistent with survey data from the 2012 ENSANUT that indicates that around 3/4 of hospitalizations occur at public hospitals); this is followed by traditional private doctors (since they are more experienced) and lastly by PADOs, since they may not be equipped to handle such cases or the doctor may not have enough experience.

Beyond the relative value, the actual functional forms of these value functions is another important assumption. Since value is bounded, I also assume that value functions are either concave or S-shaped. Under the initial assumptions above, I further assume that the value of PADOs is an increasing concave function, while the value of public and private providers has an inflection point (i.e., is convex for low severity ARIs and then becomes concave). The logic is that the value of a PADO increases sharply at first, but then becomes almost constant with severe enough cases. For the other providers, the sharp increase in value only kicks in after a certain level of severity is reached, after which value increases at a decreasing rate.

The graph on the left in Figure A4 plots the value of each provider under these assumptions as related to the severity of ARI symptoms. The vertical axis measures the value and the horizontal axis considers ARI severity. The solid line is PADOs, the dashed line is public clinics, and the dotted line is other private providers. A horizontal line denotes a value of zero, which is the outside option. Patients then choose the provider with the highest value for each level of severity.

As shown in the left-hand side plot of Figure A4, the assumptions lead PADOs to specialize in mild cases and public clinics in the most severe cases. A downside of the assumptions made is that PADO entry would only lead to substitution away from no care and from other private providers.

Hence, I consider an alternative scenario for the relative values of different providers in the second example in Figure A4. Here, I assume that the value of public care is larger than other private providers except for very severe ARI cases. This may be consistent, for instance, with situations outside normal business hours, where the public option may be an ER but the non-PADO private providers may be very expensive private hospitals. Here, one can see that without a PADO, many non-severe cases of ARIs may end up at the public ER. But once the PADO appears, only the more urgent ARI cases will end up at the ER. This could help understand the findings for ER visits. Moreover, this simple framework rationalizes part of the findings since I do not see significant substitution away from public clinics for pneumonia. Moreover, the framework exemplifies how PADOs may be pulling patients both from public clinics but also from the no-care option.

Note, however, that both of these results hinge on the strong assumptions made in each case. Also, different types of patients in different places may be facing different value functions, which in turn leads to different substitution patterns, even within the same local healthcare market. While the setup is based on some of the data patterns, some of the benefits and costs of different providers are simply unobservable (e.g., the value of time or perceived quality of care). For this reason, while this framework is useful for fixing the mind, the actual substitution patterns are an empirical question, which I address by estimating effects on utilization at public facilities.

More on the PADO doctor's financial incentives. There are two key aspects for understanding the main forces affecting PADO doctor's treatment choices. First, the fact that PADOs are vertically integrated with the pharmacy. Second, the information asymmetry between the doctors and the patients. I provide further conceptual discussions.

Vertical integration. From the pharmacy's perspective, PADOs will only be an attractive business opportunity if they can generate more profit when combined with the existing pharmacy business. In other words, the profitability of doing both the pharmacy and PADO within the boundaries of the firm should be greater than the sum of the stand-alone profitability of each. Focusing on the PADO itself, revenues from consultations are unlikely to be high enough to generate an attractive profit and, in some cases, are probably not even enough to cover the operating costs (for example, the chain *Farmacias del Ahorro* does not charge patients for consultations at their PADO, effectively making PADO revenue equal to zero). Hence, the pharmacy must be obtaining additional revenue from the drug-selling side of the business that allows them to subsidize the operation of the PADO.

This is the financial incentive for PADO doctors to overprescribe. The business model is, essentially, to have low-cost consultations that drive a higher patient volume to the pharmacy, who then buy more medications or more expensive ones (i.e., those with higher markups). This clear link between the PADO and the pharmacy is the distortion that generates misaligned incentives between patient and provider in this setting.

Asymmetric information. Patients usually do not have the same information as their doctors, and can therefore not distinguish between necessary treatments and unnecessary overprescribing. If this were not the case, patients would be able to directly monitor PADO doctors, and would therefore be more likely to discipline their prescribing behavior. In that scenario, PADO would likely cease to exist or would at least have to increase their consultation prices. Hence, the agency problem is a key driver for the financial incentives at the PADOs, precisely by allowing doctors to overprescribe patients without them being fully aware.

D 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.

E 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 A5 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 A5. 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.

Effects on share of non-urgent ER visits and share of hospitalizations coming from the ER. To better understand the effects on ER visits, I explore two features of the ER and hospital admissions data. First, there is a variable in the ER data that flags the visit as requiring urgent care. While I am unsure about how this is determined, it is a classification done by the attending physician. Unfortunately, I do not observe a physician identifier. I use this variable to construct the share of ER visits that are non-urgent, both for all diagnoses and restricting to ARIs. Second, each hospital admission has a flag for whether the patient was admitted through the ER. From this variable, I construct the share of ARI and pneumonia hospitalizations that are coming from the ER. I estimate the usual event study for these outcomes.

Figure A6 shows the results. The top graphs show a significant decline in the share of non-urgent ER visits. The effect is around 10 percentage points for all diagnoses and slightly less for ARIs. On average, around 37% of ER visits are classified as not urgent. The pre-entry estimates are all flat and close to zero.

The bottom plots show insignificant effects for the share of ARI hospital admissions coming from the ER and slightly significant effects for the share of pneumonia hospitalizations admitted through the ER. This suggests no effects on the amount of ARI cases at the ER that are transferred for inpatient care, and perhaps a small decline in the share of pneumonia hospitalizations that are being admitted through the ER.

Taken together, these results suggest that the decline in ER visits is driven mostly by a reduction in cases that are non-urgent. This is consistent with patients shifting away from the public ER to the PADO when their symptoms are not severe. Furthermore, this suggests that the decline in ER visits is consistent with decreasing wasteful visits (since ER resources would be more efficiently spent on urgent care).

Heterogeneity of effects on ARI public outpatient visits by urban locations and patient volume. Figure A7 explores effects on public outpatient clinic utilization for ARIs from the static DiD, limiting to just one PADO event per municipality. For this exercise, I randomly choose one PADO entry per municipality and estimate the static DiD regression. I repeat this 100 times and plot the distribution of effects. The plot on the left in Figure A7 considers a 2-year window around entry, while the one on the right includes the full sample. A solid marker represents the full effect estimated in the main text (Table 2). For the 2-year window sample, restricting to one event per municipality yields a larger effect in absolute value. For the full sample, the average effect is zero.

Figure A8 explores how the static DiD effect in Table 2 varies by the number of nearby public outpatient clinics. Some PADOs enter local markets with many nearby public clinics (which are presumably more urban areas), while others enter markets with few nearby clinics (i.e., more isolated). I explore heterogeneous effects along this dimension. I interact the post-entry indicator with the number of matched clinics and with its square and estimate the static DiD equation. Figure A8 then plots the estimated effects by percentile of the number of nearby public clinics. I find that the substitution effects are concentrated in local markets that are more urban, as measured by the number of nearby public clinics.

Panel A in Table A5 further explores effects by urban vs rural (less urban) locations, based on the municipality where entry takes place. I stratify PADO events into those occurring in urban and non-urban municipalities using two definitions: (i) the official government definition based on population counts, and (ii) the median percentage of rural population according to the census data (for the municipalities with PADO entry). I estimate the static DiD equation from Table 2, interacting the post-entry indicator with the urban indicator. I show results for different samples (2-year window around entry, full sample, and 48-week window around entry). I find mostly negative coefficients across the board, though not all are significant. A test of whether the effects in urban and non-urban areas are equal does not reject that they are the same. Hence, stratifying by municipalities that are more vs less urban yields statistically similar effects.

Lastly, Panel B in Table A5 stratifies PADO events by the baseline volume of patients at the matched public clinics. I consider the number of visits at public clinics during the year prior to entry and stratify on the median. This measure may correlate with urbanicity, but also reflects high demand areas and potential congestion. I follow the same strategy as above. Point estimates for the low patient volume markets are positive and small, while effects are negative and significant for markets with high baseline patient volume. A test allows me to reject that the effect sizes are equal. This suggests that substitution occurs in markets that are (possibly) more congested.

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 A6 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 A7 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 A8 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 A7.

The last two columns in Table A8 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.

Effects on in-hospital deaths. Figure A9 explores whether PADO entry is associated with changes in in-hospital deaths for a variety of conditions. I consider two outcomes: the inverse hyperbolic sine of death counts and the death rate defined as the number of deaths per 1,000 hospital admissions. I follow the event study estimation strategy from the main text. I show results for all diagnoses, ARIs, pneumonia, GIDs, and chronic conditions.

For all diagnoses, I find a slight (but insignificant) decline in in-hospital deaths, although there are no effects for the death rate. For ARIs, pneumonia, and chronic conditions, I do not see any effects in terms of the counts or the rates. For GIDs, I again do not see any effects for the death counts, although there does seem to be a slight, temporary increase in the death rate at around 40 weeks post-entry. Note, however, that this effect is not significant at conventional levels.

Overall, the results in Figure A9 suggest that there are no changes in in-hospital deaths following PADO entry.

Associations with death rates (vital statistics records). I explore the relationship between the number of PADOs per capita (at the municipality level) and death rates in Table A9. I obtain vital statistics data from the Mexican statistics office INEGI. This information is obtained directly from death certificates. I use deaths that occurred from 2005 to 2015. The data identify the main cause of death using ICD-10 codes, from which I obtain the municipality-month counts of ARI and pneumonia deaths. I then divide by population to obtain the death rate per 10,000 people. Estimates correspond to a regression of the death rate on total PADOs per 10,000 people, with municipality and monthly date FE. Different columns consider different specifications. Standard errors are clustered by municipality.

Panel A in Table A9 shows that there is no significant association between PADOs and ARI death rates. Estimates are all very small and insignificant. Panel B shows similar results for pneumonia. Auxiliary regressions (not shown) consider other diagnoses (i.e., GIDs and chronic conditions) and find similar null effects. These findings suggest that PADOs are not leading to an increase in deaths (although death rates are also not declining).

Standard TWFE event studies. For transparency, this robustness check shows the traditional TWFE event study plots, regressing the outcome on a vector of leads and lags of entry, with PADO and time FE. Standard errors are clustered at the PADO event level. Event study estimates are shown with six four-week periods on either side of entry, and include indicators for all remaining periods before and after this window. Overall, these estimates paint a similar picture to the ones presented in the main text.

Figure A10 considers the main results concerning ARI healthcare utilization at public outpatient clinics, SSA ERs, and SSA hospitals. The first plot shows that 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. Note that changing the reference period (for example, to 8 weeks prior to entry) would lead to a mostly insignificant effect post-entry (except perhaps for 12 weeks after entry). However, the point estimates alone do seem to suggest a decline in visits post-entry, and both the simple DiD regression and the robust estimators in the main text also indicate a significant decline in ARI visits.

The second plot in Figure A10 considers the impact on 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 last plot in Figure A10 shows results for ARI hospital admissions. 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.

Figure A13 repeats the exercise for other conditions at public outpatient clinics. For pneumonia, 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. For GIDs, estimates are mostly zero and insignificant, suggesting no changes in GID visits. For chronic conditions, estimates are zero and insignificant prior to entry, 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. Lastly, the estimates for all visits show a significant decline in total outpatient visits.

Figure A14 shows results for ER visits due to other conditions. For pneumonia, there is a significant decline in visits of around 26%. For GIDs, the decline in visits is significant and around 46%. For chronic conditions, there is perhaps a small decline in SSA ER visits after PADO entry, although estimates are not significant. Lastly, there is a large and significant decrease in visits for any cause.

Figure A15 considers hospital admissions. For pneumonia, there is a gradual and significant decline in pneumonia hospitalizations. For GIDs, there is somewhat of a decline in admissions although the parallel trends assumption only seems to hold up to 16 weeks prior to entry. For chronic conditions, there may be a bit of a decline after 23 weeks of entry, but again the parallel trends assumption only seems to hold for up to three months before entry. Lastly, there seems to be a dip in total admissions in the first few weeks post-entry that then reverts back to zero.

Larger catchment areas for ERs and hospitals. It is possible that a 5 km radius is too small a catchment area for ERs and hospitals. One indication of this may be the large number of outpatient clinics relative to the number of ERs and hospitals. I explore whether results differ when considering larger catchment areas for ERs and hospitals. I replicate the DiD effects shown in Table 2 with progressively larger catchment areas, going all the way up to a 10 km radius. Estimates for ER visits and hospital admissions are shown in Figure A11. The main results are robust to constructing larger radii for ERs and hospitals.

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 A12 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.

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 A16 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 A16. 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.

Associations between PADOs and penicillin sales over time. The penicillin sales analysis covers the period from 2010 to 2012. The antibiotics prescriptions law that was implemented in August 2010 prohibited over-the-counter sales of antibiotics. If we believe that patients with less severe symptoms would buy narrow spectrum penicillin prior to the law, then it is possible that these same patients would rather not visit a doctor post-law (since their symptoms are mild). Likewise, one may observe that those that do decide to go to the doctor may now end up with a prescription for a broad spectrum penicillin. Hence, the effect of an increase in PADOs may be confounded with this law.

To address this potential issue, I estimate regressions similar to the main estimates in Table 4, allowing for differential effects in 2010 vs the 2011-2012 period. These results are shown in Table A11. Across specifications, I find strong evidence of an increase in broad spectrum penicillin sales when the total number of PADOs increases in the post-law period (starting in 2011 when one would expect the impact of the law alone to have stabilized). Likewise, there is a strong negative association between PADOs and narrow spectrum sales in this time period. Results for the 2010 period are weaker, perhaps due to this potentially confounding effect. Overall, Table A11 provides evidence suggesting that the shifts in penicillin prescriptions hold even after the immediate and direct effects of the law have passed.

Associations between PADOs and penicillin sales by low- vs high-price products. I classify penicillin products as having an average price over the three-year period that is low (below the median) vs high (above the median). I then estimate regressions similar to the main estimates in Table 4, allowing for differential effects for low- vs high-price products within each type (narrow and broad spectrum).

I show the estimates in Figure A17. The plot on the left considers the base specification. Each marker shows a coefficient and the bars denote 95% confidence bands. I find that the negative association between PADOs and narrow spectrum penicillin is driven by products that have an average price below the median. The point estimate for high-priced narrow spectrum penicillin is very close to zero, while the one for low-price products is negative and significant. For broad spectrum, I obtain a larger (positive) point estimate for high-price products, although a test of equality does not allow me to reject that the low- and high-price coefficients are equal.

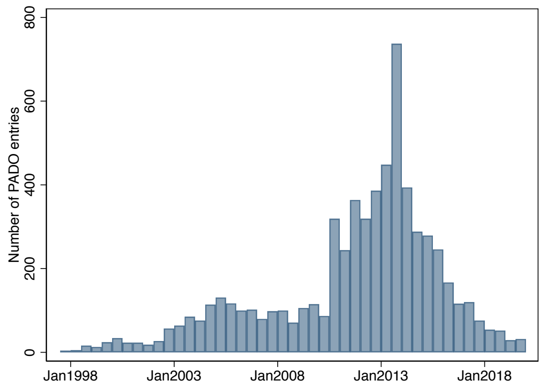
The plot on the right adds product-by-time period FE. Results are similar for narrow spectrum penicillin, with the negative association driven entirely by the low-price products. For broad spectrum, I again find that the high-price coefficient is positive and significant, but now the low-price coefficient is negative (and small) and statistically indistinguishable from zero. A test allow me to reject that these effects are equal.

Overall, the estimates in Figure A17 show that the negative association between PADOs and narrow spectrum penicillin is driven by the low-price products, while the positive association between PADOs and broad spectrum penicillin is driven by high-price products. This is consistent with the PADOs responding to a financial incentive in their prescribing behavior.

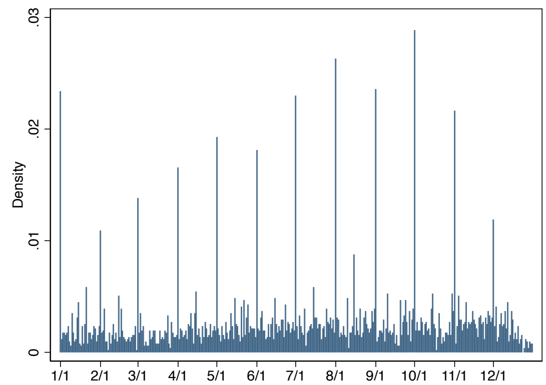
F Time Series of Penicillin Sales

Figure A18 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

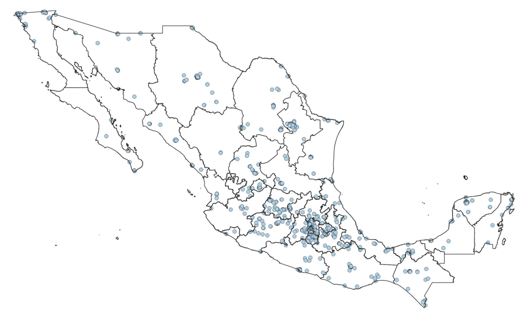


(b) Within year distribution of entries

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

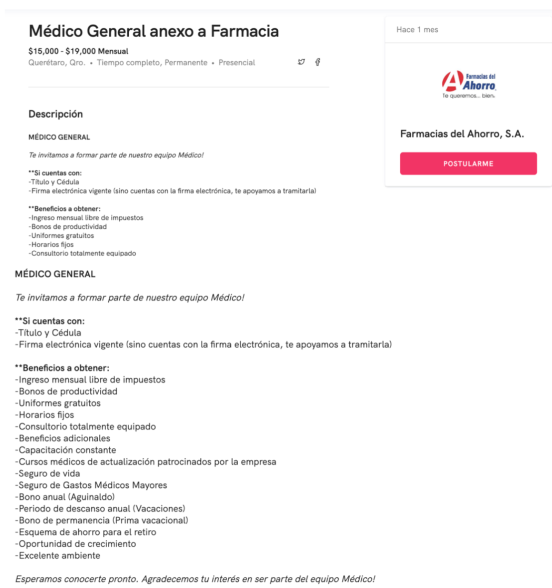
(d) 2016 to 2019

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:
Examples of Payment Schemes for Doctors at PADOs

(a) Example 1

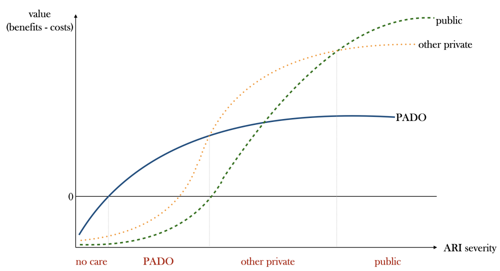
(b) Example 2



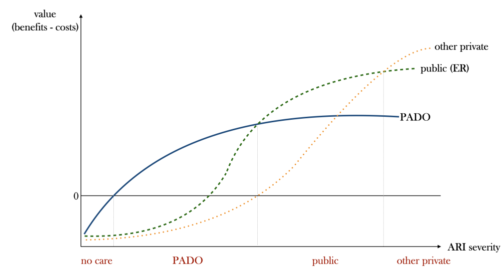
(c) Example 3

Notes: This figure shows examples of job postings for medical personnel at PADOs. All three ads were taken from the commonly used website OCC (occ.com.mx) between August 29 and September 2, 2022. Example 1 describes a base salary plus extras from visits and procedures like taking the patients blood pressure. Example 2 talks about a bonus that can vary and about extras by daily patient volume. Example 3 offers a productivity bonus.

Figure A4:
Conceptual Framework: Value of Different Providers and ARI Severity



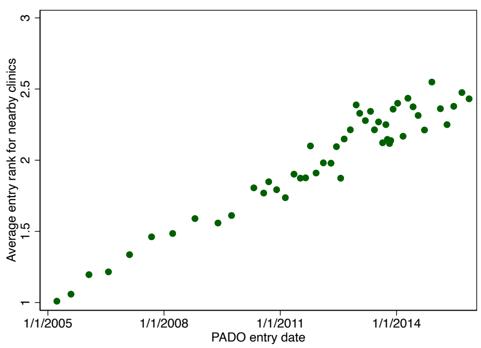
(a) Example 1



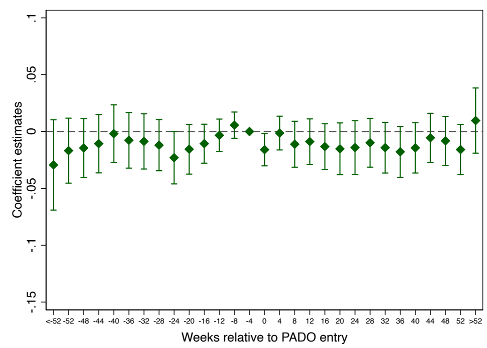
(b) Example 2

Notes: These graphs show the value of seeking care at different providers (defined as the benefit minus the cost) as a function of disease severity. The solid line represents healthcare at PADOs, the dashed line is public outpatient clinics, and the dotted line considers other private providers. The value of not seeking care is zero. Patient choices by severity are determined by the option with the maximum value and are shown in red font. Each plot shows different assumptions for the functional form of the value of care at different providers.

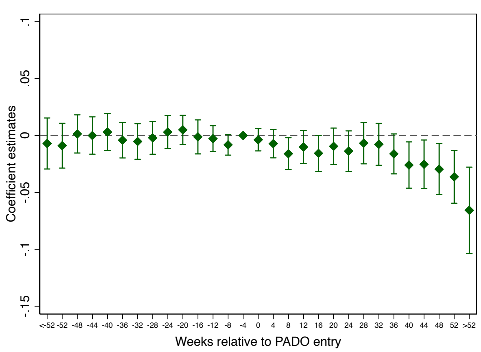
Figure A5:
Entry Rank of Matched Clinics and the Effect of PADO Entry on
ARI Utilization at Public Outpatient Clinics



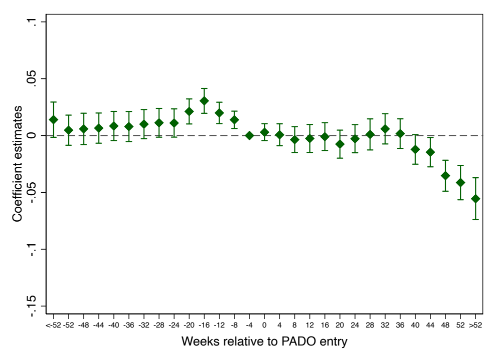
(a) Average rank by entry date



(b) Bottom tercile of average rank



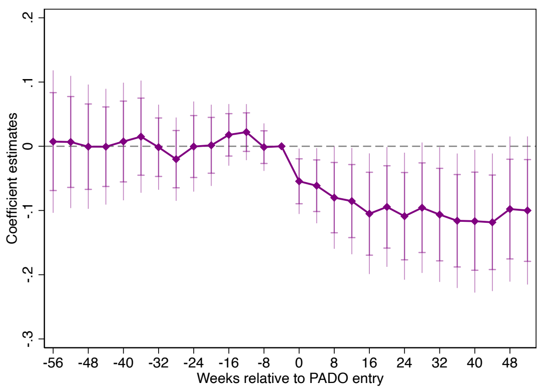
(c) Middle tercile of average rank



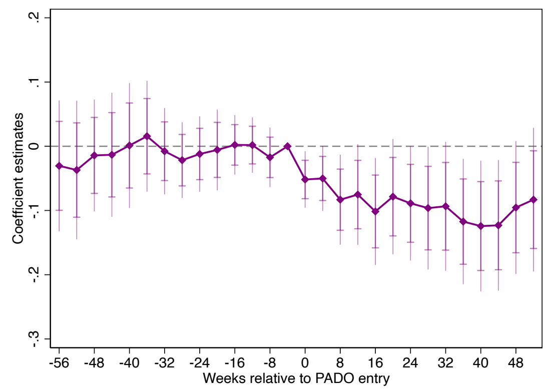
(d) Top tercile of average rank

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.

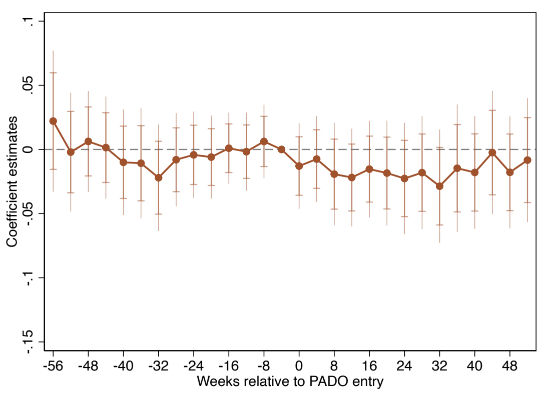
Figure A6:
Effects on Share of Non-Urgent ER Visits and on Share of
Hospital Admissions from ER



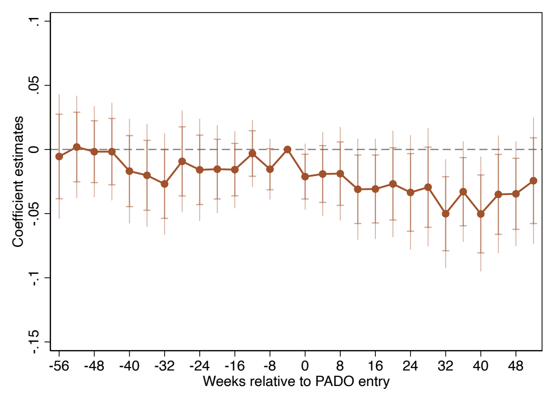
(a) Share non-urgent ER visits



(b) Share non-urgent ARI ER visits



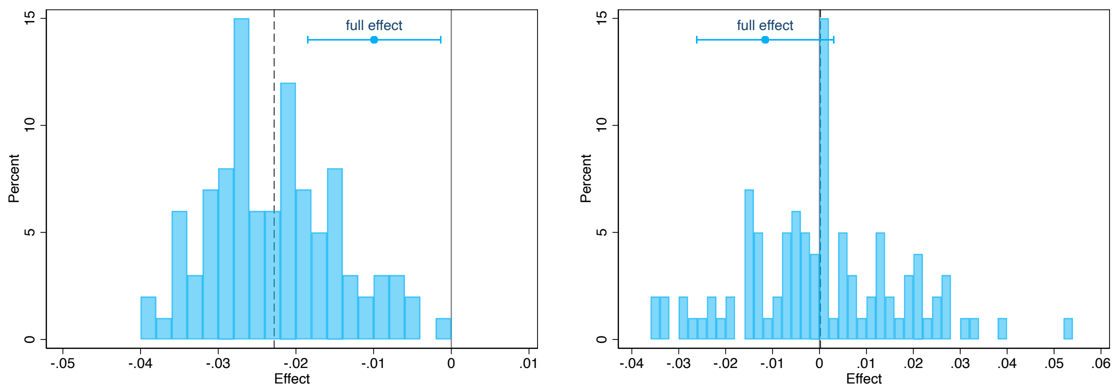
(c) Share ARI hosp. from ER



(d) Share pneumonia hosp. from ER

Notes: These plots show event studies of PADO entry on the share of SSA emergency room visits classified by the attending physician as not requiring urgent care, and on the share of SSA hospital admissions that are coming through the ER. Each graph shows the coefficients from regressing the corresponding share on a vector of leads and lags of PADO entry, with PADO and time period FE, using DiD estimators robust to heterogeneous ATE (see text for details). Capped spikes represent 95% confidence bands constructed from 100 bootstrap repetitions with robust standard errors clustered at the PADO level, while uncapped spikes show uniform confidence bands (see text for details).

Figure A7:
Robustness of Effect on ARI Visits to Restricting to One PADO Event per Municipality

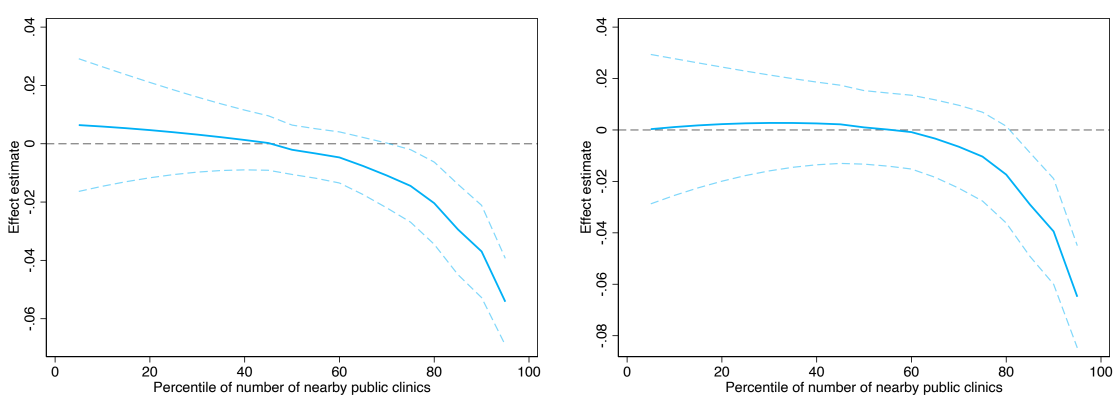


(a) 2-year window around entry

(b) Full sample

Notes: These plots show the DiD effect of PADO entry on healthcare utilization for ARIs at public outpatient clinics restricting to one PADO event per municipality. I randomly choose one PADO event per municipality and estimate a regression of the inverse hyperbolic sine of ARI visits on an indicator for post-entry, with PADO and time period FE. The histogram plots the distribution of coefficients obtained from this exercise over 100 iterations. The vertical dashed line shows the average effect size. The solid marker shows the full effect as presented in Table 2, with a 95% confidence interval (robust standard errors clustered at the PADO level).

Figure A8:
Heterogeneity of Effect on ARI Visits by Number of Matched Public Outpatient Clinics

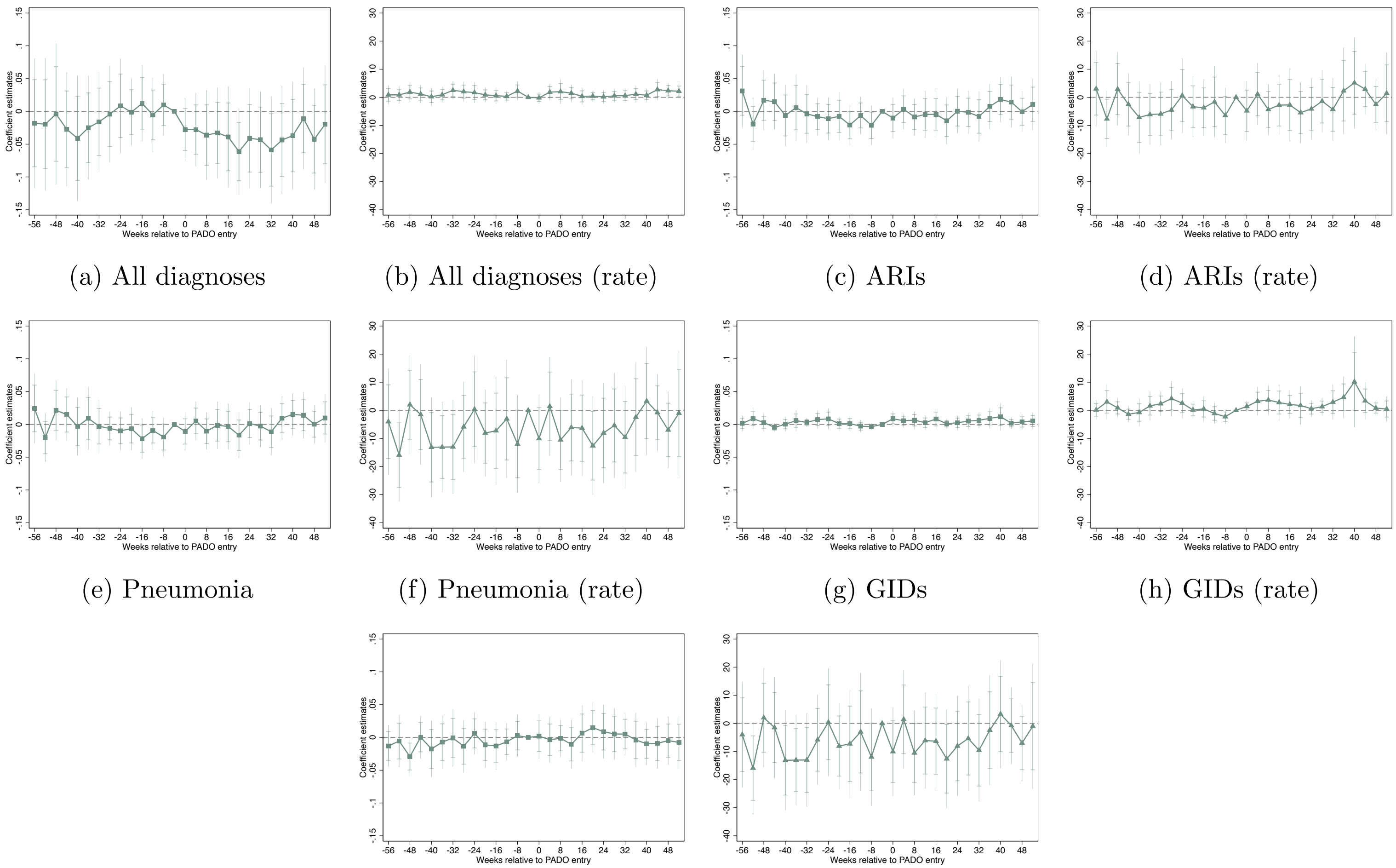


(a) 2-year window around entry

(b) Full sample

Notes: These plots show the DiD effect of PADO entry on healthcare utilization for ARIs at public outpatient clinics by percentile of the number of matched public outpatient clinics. I estimate a regression of the inverse hyperbolic sine of ARI visits on an indicator for post-entry, an interaction of this indicator with the number of matched public outpatient clinics (within 5 km), a similar interaction with the square of matched clinics, and PADO and time period FE. The plot shows the estimated effect by percentile of the number of matched clinics. The dashed lines represent the 95% confidence interval (robust standard errors clustered at the PADO level).

Figure A9:
SSA Hospital Deaths and PADO Entry



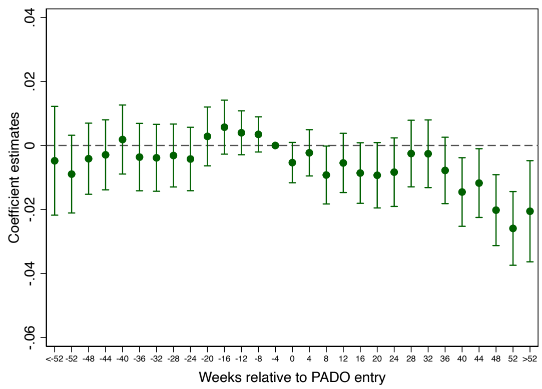
(a) All diagnoses (b) All diagnoses (rate) (c) ARIs (d) ARIs (rate)

(e) Pneumonia (f) Pneumonia (rate) (g) GIDs (h) GIDs (rate)

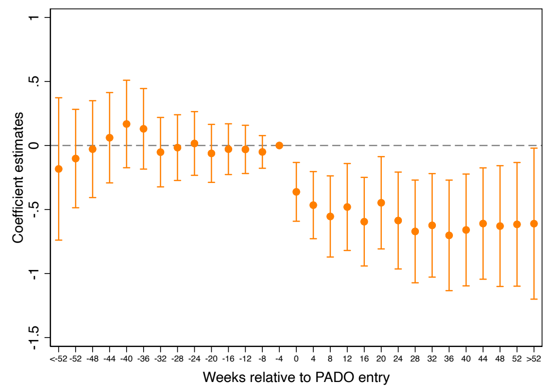
(i) Chronic conditions (j) Chronic (rate)

Notes: These plots show event studies of PADO entry on SSA hospital deaths by diagnosis (444 events from 2005 to 2015). For each category of diagnoses, I use two outcomes: the inverse hyperbolic sine of death counts and the death rate defined as number of deaths per 1,000 hospital admissions. Each graph shows the coefficients from regressing the corresponding outcome on a vector of leads and lags of PADO entry, with PADO and time period FE, using DiD estimators robust to heterogeneous ATE (see text for details). Capped spikes represent 95% confidence bands constructed from 100 bootstrap repetitions with robust standard errors clustered at the PADO level, while uncapped spikes show uniform confidence bands (see text for details).

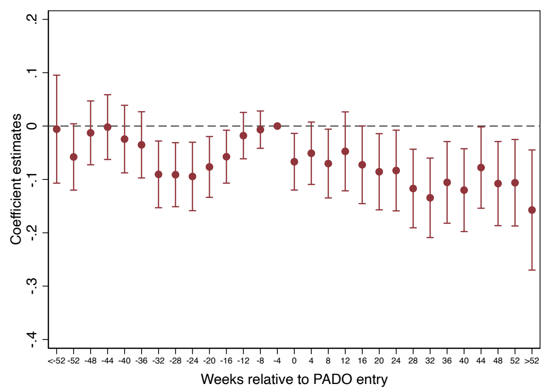
Figure A10:
Standard TWFE Event Studies for Public Healthcare Utilization
for ARIs



(a) Outpatient clinic visits



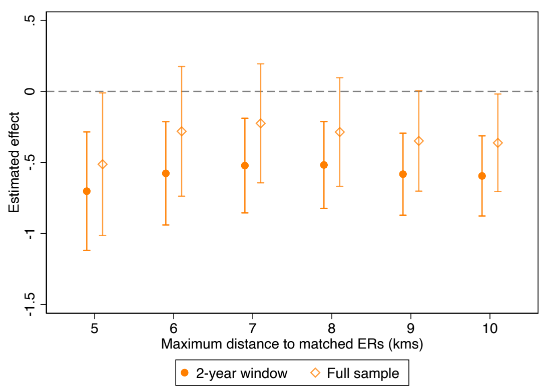
(b) SSA ER visits



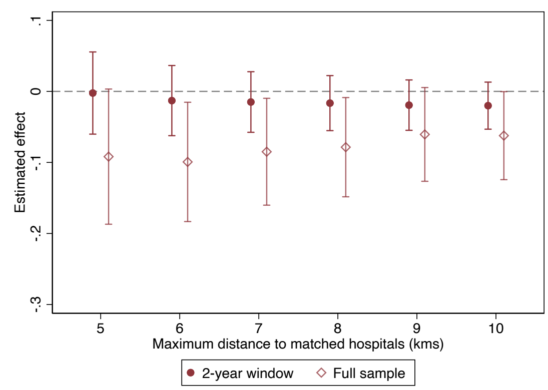
(c) SSA hospital admissions

Notes: These plots show standard TWFE event studies 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 around entry, controlling for PADO and period FE. Spikes represent 95% confidence bars from robust standard errors clustered at the PADO event level. The outcome variables are the inverse hyperbolic sine of public outpatient clinic visits, SSA ER visits, and SSA hospitalizations, respectively.

Figure A11:
Robustness to Larger Radii for ER and Hospital Matches



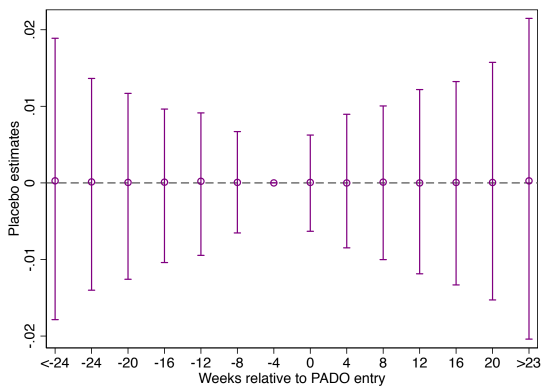
(a) Effect on ER visits for ARIs



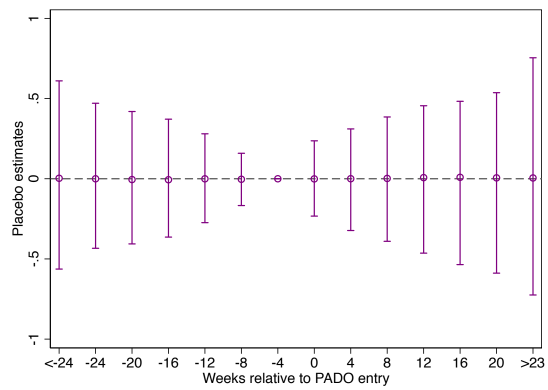
(b) Effect on hospital admissions for ARIs

Notes: These plots show estimates for different radii for assigning ERs and hospitals to the PADO entries. The first estimate (at most 5 km) corresponds to the main result shown in Table 2. Each coefficient shows the corresponding DiD effect for each sample, regressing the the inverse hyperbolic sine of ARI visits or admissions on an indicator for post-entry, with PADO and time period FE, with robust standard errors clustered at the PADO level. Spikes show 95% confidence bars. The bold coefficients correspond to effects considering just a 2-year window around entry, while the lighter, hollow series includes the entire sample.

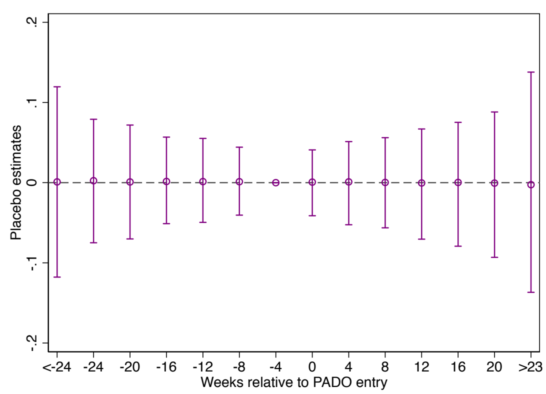
Figure A12:
Placebo Estimates from Randomly Shuffled Entry Dates for
Public Healthcare Utilization due to ARIs



(a) Outpatient clinic visits



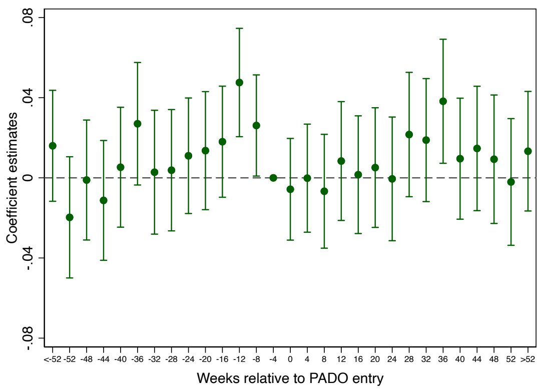
(b) SSA ER visits



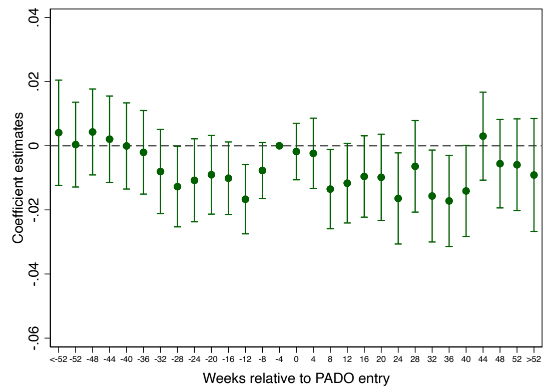
(c) SSA hospital admissions

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 bars.

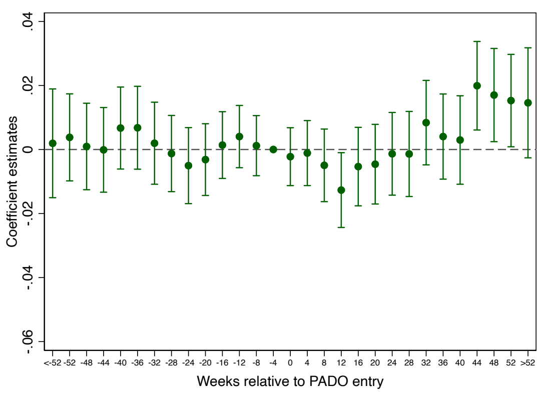
Figure A13:
Standard TWFE Event Studies for Public Outpatient Clinic
Utilization for Other Conditions



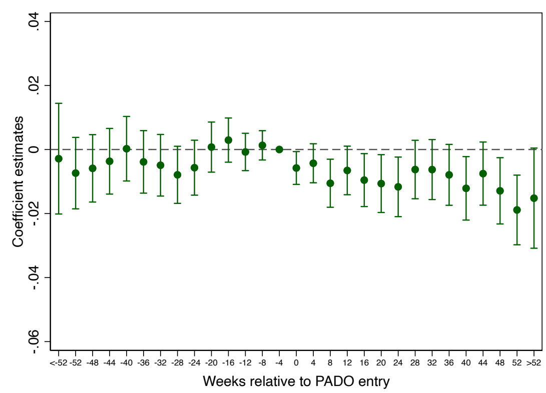
(a) Pneumonia (2007-2014)



(b) GIDs



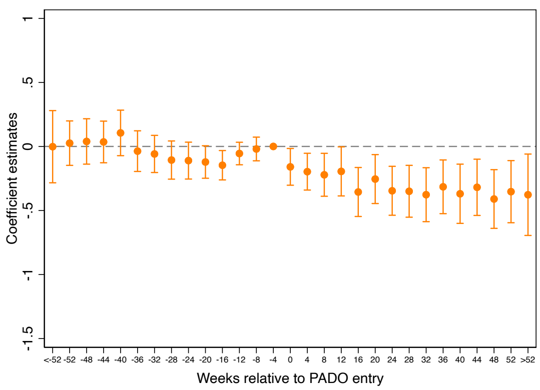
(c) Chronic conditions



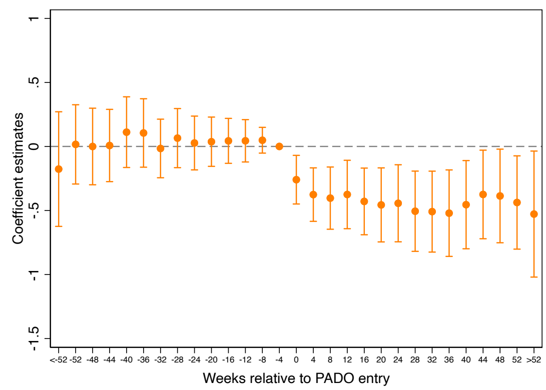
(d) All diagnoses

Notes: These plots show standard TWFE event studies for the effect of PADO entry on public outpatient clinic utilization for conditions different than ARIs. PADOs are matched with public outpatient clinics within a 5 km radius to construct aggregates of utilization. Each plot considers lead and lag estimates around entry, controlling for PADO and period FE. Spikes represent 95% confidence bars from robust standard errors clustered at the PADO event level. The outcome variables are the inverse hyperbolic sine of visits.

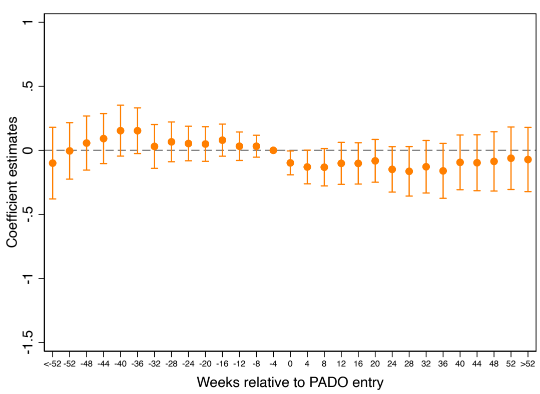
Figure A14:
Standard TWFE Event Studies for SSA ER Visits for Other Conditions



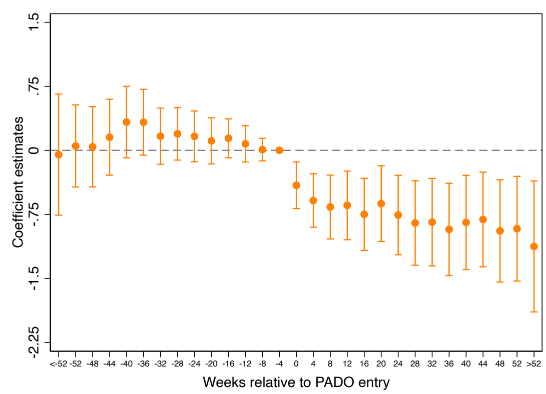
(a) Pneumonia



(b) GIDs



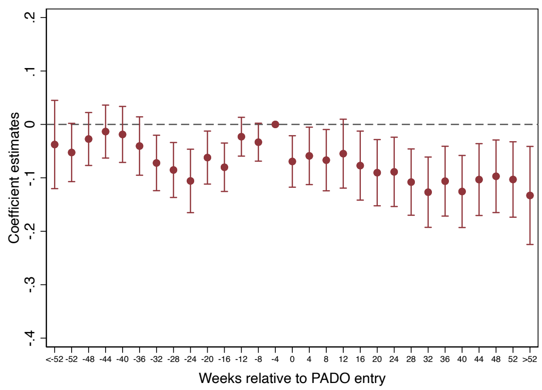
(c) Chronic conditions



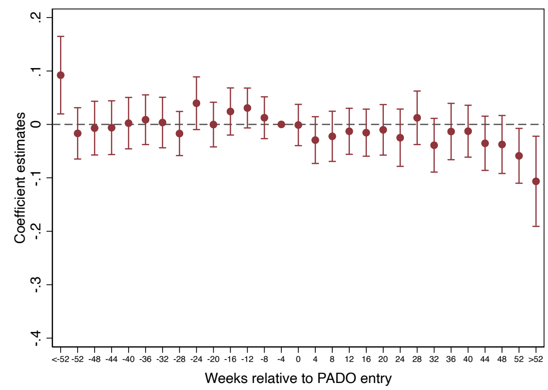
(d) All diagnoses

Notes: These plots show standard TWFE event studies 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 around entry, controlling for PADO and period FE. Spikes represent 95% confidence bars from robust standard errors clustered at the PADO event level. The outcome variables are the inverse hyperbolic sine of SSA ER visits.

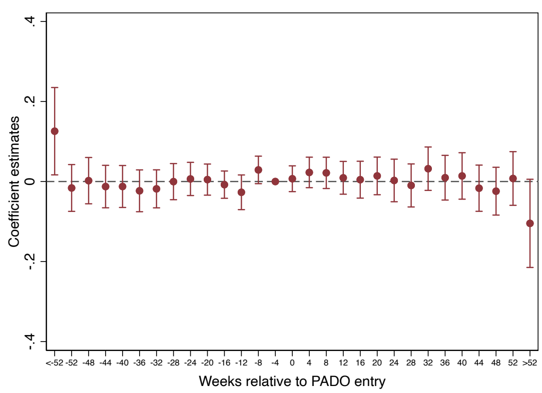
Figure A15:
Standard TWFE Event Studies for SSA Hospital Admissions for Other Conditions



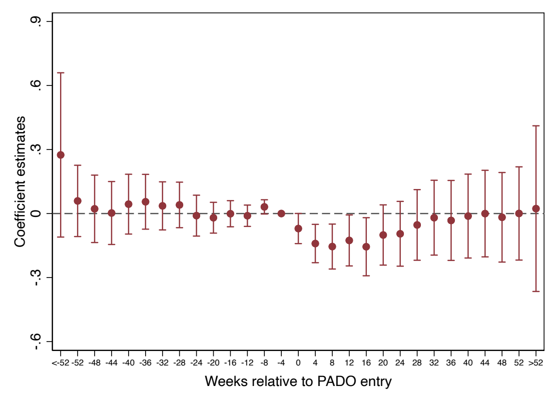
(a) Pneumonia



(b) GIDs



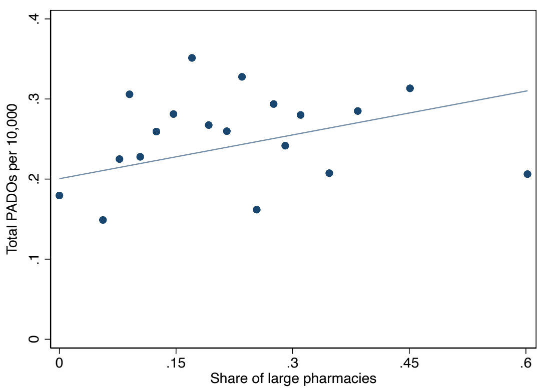
(c) Chronic conditions



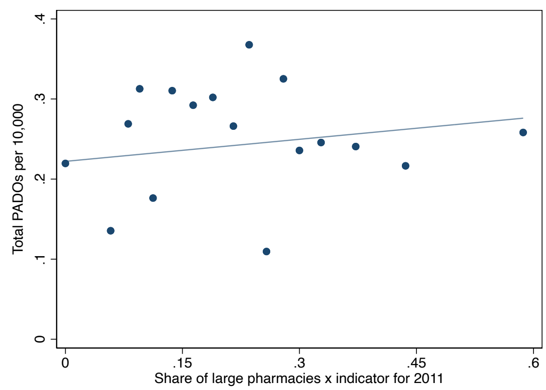
(d) All diagnoses

Notes: These plots show standard TWFE event studies 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 around entry, controlling for PADO and period FE. Spikes represent 95% confidence bars from robust standard errors clustered at the PADO event level. The outcome variables are the inverse hyperbolic sine of SSA hospital admissions.

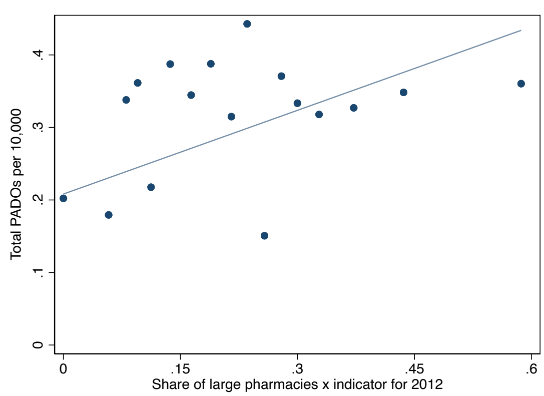
Figure A16:
Correlation between PADOs per Capita and Share of Large Pharmacies



(a) Share of large pharmacies



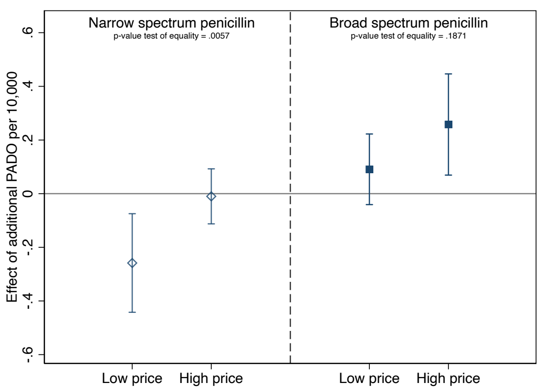
(b) Share of large pharmacies × 2011



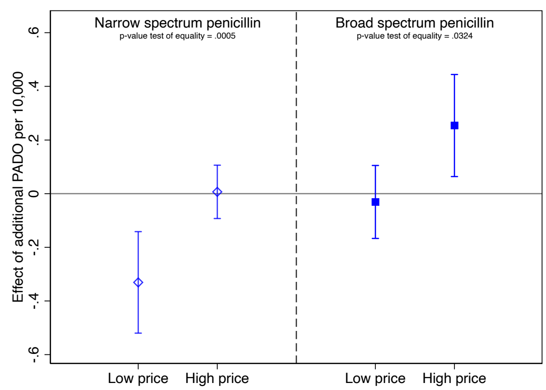
(c) Share of large pharmacies × 2012

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 A17:
Asssociations between PADOs and Penicillin Sales by Low vs
High Price Products



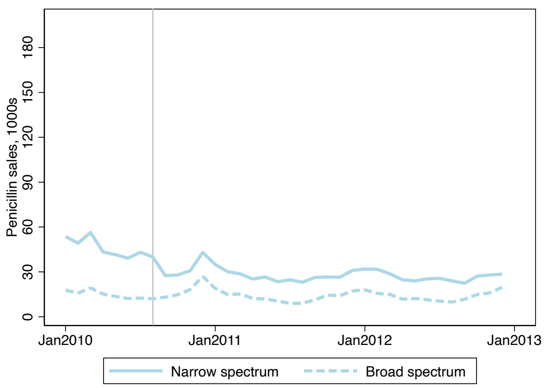
(a) Baseline specification



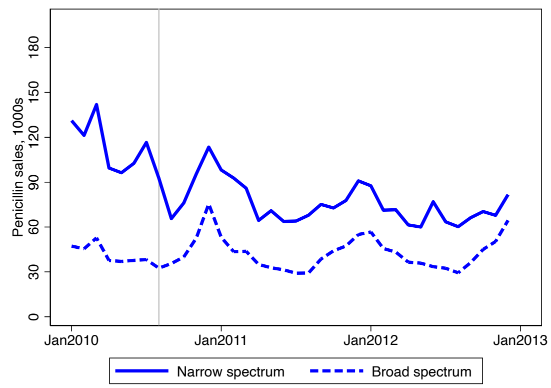
(b) Product $\times$ time period FE

Notes: These plots show estimates of the association between PADOs per capita and penicillin sales by high- vs low-price products, using the full data at the product-municipality-time period level and the inverse hyperbolic sine of units sold as the outcome variable. Effects are estimated by type of penicillin (narrow vs broad spectrum) and by price (product has average price below vs above the median). Coefficient tests of whether the effects are statistically different between the low- and high-price products by type are shown. The plot on the left uses the base specification that regresses the outcome on PADOs per capita, with product, municipality, and time period FE. The plot on the right adds product-time period FE. Bars denote 95% confidence intervals from robust standard errors clustered at the municipality level.

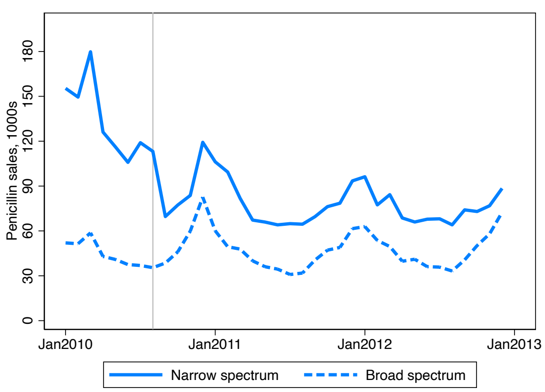
Figure A18:
Time Series of Penicillin Sales



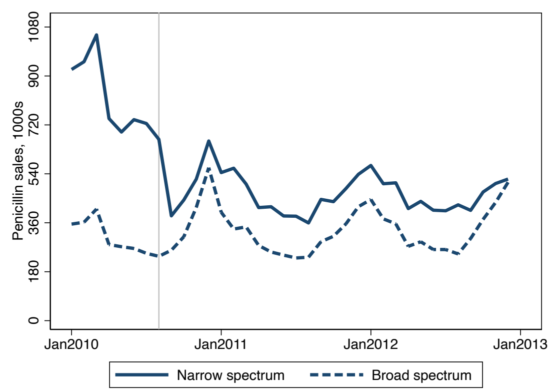
(a) Municipalities with zero PADOs



(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:
Heterogeneity of Effect on ARI Visits by Urban Locations and Patient Volume

	2-year window	Full sample	48-week window	2-year window	Full sample	48-week window
Panel A: Semi-urban vs urban locations						
After PADO entry × semi-urban area	0.1040	0.0068	0.1083	-0.0109	-0.0468**	-0.0088
	(0.0745)	(0.1107)	(0.0786)	(0.0185)	(0.0207)	(0.0166)
After PADO entry × urban area	-0.0109**	-0.0117	-0.0080**	-0.0098**	-0.0061	-0.0067*
	(0.0044)	(0.0075)	(0.0038)	(0.0046)	(0.0077)	(0.0040)
Observations	438,552	730,873	232,670	438,552	730,873	232,670
R-squared	0.9555	0.9374	0.9671	0.9555	0.9375	0.9671
Urban definition	INEGI	INEGI	INEGI	Median	Median	Median
Share rural	0.0086	0.0092	0.0088	0.137	0.140	0.138
Mean dep. var. rural area	247.4	234.3	249.7	659.6	642	661
Mean dep. var. urban area	4,981	4,854	4,952	5,617	5,488	5,591
Equality of coefficients test	0.126	0.868	0.142	0.954	0.057	0.903
Panel B: Baseline volume of patients						
After PADO entry × low volume	0.0091	0.0097	0.0013			
	(0.0073)	(0.0102)	(0.0062)			
After PADO entry × high volume	-0.0299***	-0.0340***	-0.0153***			
	(0.0055)	(0.0084)	(0.0045)			
Observations	438,552	730,873	232,670			
R-squared	0.9556	0.9375	0.9671			
Mean dep. var. low volume	1,701	1,630	1,690			
Mean dep. var. high volume	8,219	7,927	8,191			
Equality of coefficients test	0.000	0.000	0.034			

Notes: This table shows heterogeneous effects of the DiD effect of PADO entry on ARI visits at public outpatient clinics. Panel A considers urban vs less urban (or semi-urban) locations. Panel B considers the baseline volume of patients. I regress the inverse hyperbolic sine of ARI visits on an indicator for post-entry interacted with the relevant dimensions, and PADO and time period FE. Standard errors are clustered at the PADO event level. Panel A considers two definitions of urbanicity: the official government definition provided by INEGI and a data-driven indicator of having a share of "rural" population above the median (i.e., in the census, this means the fraction of people in the municipality living in localities with less than 2,500 individuals). Panel B stratifies clinics based on the median patient volume in the year prior to PADO entry to obtain heterogeneous effects for events where volume was above vs below the median. Means of the dependent variable by group shown. A test of whether the effects are statistically equal in both groups is also shown.
*** p<0.01, ** p<0.05, * p<0.1

Table A6:
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 A7:
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 A8:
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.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A9:
Estimates of PADOs on ARI and Pneumonia Death Rates from Vital Statistics Records

	Base specification	+ state-specific trends	Ever-PADO sample
Panel A: ARI deaths			
Total PADOs per 10,000	0.0078	0.0069	0.0091
	(0.0080)	(0.0077)	(0.0083)
Observations	276,134	276,134	98,856
R-squared	0.0661	0.0665	0.1724
Mean dependent variable	0.122	0.122	0.121
Panel B: Pneumonia deaths			
Total PADOs per 10,000	0.0083	0.0068	0.0082
	(0.0078)	(0.0076)	(0.0081)
Observations	276,134	276,134	98,856
R-squared	0.0629	0.0632	0.1632
Mean dependent variable	0.105	0.105	0.105

Notes: This table shows estimates of the association between PADOs per capita and death rates from vital statistics data from 2005 to 2015. Observations are at the municipality-month level. Panel A considers ARI deaths per 10,000 people. Panel B shows pneumonia deaths per 10,000 people. Estimates are shown from regressing each outcome on PADO counts per 10,000, with municipality and monthly date FE. The baseline specification includes a differential trend for municipalities that have at least one PADO at some point during the sample period. The second column adds differential linear trends by state. The last column restricts the sample to municipalities that ever get at least one PADO during this period. Means of the dependent variables shown. Robust standard errors in parentheses, clustered at the municipality level.
*** p<0.01, ** p<0.05, * p<0.1

Table A10:
Associations between PADOs and Total Penicillin Sales

	Base spec.	Product-time period FE	Mun.-prod. FE + PADO trend	Excl. Mexico City	Muns. with PADOs only
PADOs per 10,000	-0.012	-0.045	-0.010	-0.003	-0.010
	(0.049)	(0.046)	(0.051)	(0.051)	(0.051)
Observations	1,381,464	1,381,140	1,381,464	1,333,116	1,106,064
R-squared	0.540	0.579	0.797	0.793	0.802
Mean dependent variable	30.58	30.58	30.58	27.59	36.70
Mean PADOs per 10,000	0.204	0.204	0.204	0.203	0.284
Mean PADOs	3.83	3.83	3.83	3.62	5.32

Notes: This table shows estimates of the association between PADOs per capita and penicillin sales, without distinguishing by types of penicillin. Data are at the product-municipality-time period level. The outcome variable is the inverse hyperbolic sine of units sold of a product in a municipality-time period. 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. 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.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A11:
Associations between PADOs and Penicillin Sales by Time Period

	Base spec.	Product-time period FE	Mun.-prod. FE + PADO trend	Excl. Mexico City	Muns. with PADOs only
Total PADOs per 10,000 × narrow spectrum × 2010	-0.100	-0.155**	-0.053	-0.055	-0.053
	(0.069)	(0.066)	(0.067)	(0.068)	(0.067)
Total PADOs per 10,000 × broad spectrum × 2010	0.001	0.050	-0.092	-0.082	-0.092
	(0.079)	(0.076)	(0.069)	(0.070)	(0.069)
Total PADOs per 10,000 × narrow spectrum × 2011-2012	-0.151**	-0.167***	-0.082	-0.079	-0.082
	(0.060)	(0.060)	(0.058)	(0.058)	(0.058)
Total PADOs per 10,000 × broad spectrum × 2011-2012	0.213***	0.151***	0.122**	0.137***	0.122**
	(0.056)	(0.055)	(0.050)	(0.050)	(0.050)
Observations	1,381,464	1,381,140	1,381,464	1,333,116	1,106,064
R-squared	0.541	0.580	0.797	0.793	0.802
Tests of equality of coefficients 2010 vs 2011-2012:					
Narrow spectrum effects	0.190	0.779	0.490	0.581	0.490
Broad spectrum effects	0.000	0.019	0.000	0.000	0.000
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
Mean PADOs per 10,000	0.226	0.226	0.226	0.224	0.282
Mean PADOs	5.583	5.580	5.583	5.292	6.973

Notes: This table shows estimates of the association between PADOs per capita and penicillin sales, using the full data at the product-municipality-time period level and the inverse hyperbolic sine of units sold as the outcome variable. Effects are estimated by type of penicillin (narrow vs broad spectrum) and by date (2010 vs 2011-2012). 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. Robust standard errors clustered at the municipality level are shown in parentheses. Coefficient tests are shown for whether the effects estimated in 2010 and in 2011-2012 are equal. 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.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$