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The Economics of the Public Option: Evidence from Local Pharmaceutical Markets*

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Abstract. We study the economic and political effects of competition by state-owned firms, leveraging the decentralized entry of public pharmacies to local markets in Chile around local elections. Public pharmacies sell drugs at a third of private pharmacy prices, because of a stronger upstream bargaining position and downstream market power in the private sector, but are also of lower quality. Exploiting a field experiment and quasi-experimental variation, we show that public pharmacies affected consumer shopping behavior, inducing market segmentation and price increases in the private sector. This segmentation created winners and losers, as consumers who switched to public pharmacies benefited, whereas consumers who stayed with private pharmacies were harmed. The countrywide entry of public pharmacies would reduce yearly consumer drug expenditure by 1.6 percent, which outweighs the costs of the policy by 52 percent. Mayors that introduced public pharmacies received more votes in the subsequent election, particularly by the target population of the policy.

Keywords. competition, state-owned firms, pharmacies, political returns
JEL codes. D72, H4, I16, L3

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1 Introduction

State-owned firms compete with the private sector in a variety of markets, including education, healthcare, insurance, and basic services. Supporters of the public option argue that it helps discipline markets that fail to provide enough incentives for private competition, either because of information asymmetries, market power, collusive behavior, or other market failures (Atkinson and Stiglitz, 1980). Additionally, the state can use its bargaining power to decrease input prices, particularly when upstream markets are imperfectly competitive. However, critics claim that the state can be less efficient than private firms and express concerns about the potential use of these services for clientelism (Shleifer and Vishny, 1994; Shleifer, 1998). Tackling this trade-off empirically has been difficult due to the lack of exogenous variation in the extent of public competition, and the scarcity of contexts that allow an evaluation of both the market and political aspects.

In this paper, we study the decentralized and large-scale entry of public retail pharmacies in Chile. Around the 2016 local elections, public pharmacies emerged as competition from local governments to a fully deregulated and highly concentrated private retail market characterized by high prices.[1] Public pharmacies are non-profit, managed by local governments and sell drugs to people who live in their counties at prices that are, on average, 34 percent of those charged at their private counterparts. These price differences relate to two attributes of this market. First, private pharmacies hold substantial market power in the retail market, which translates into large markups. Second, public pharmacies hold a cost advantage because they can purchase through the public intermediary. This setting, combined with detailed data on individual and aggregate economic and political outcomes, provides a unique opportunity to study the effects of state-owned firms.

Between 2015 and 2018, public pharmacies entered 147 of the 345 counties in the country. Public pharmacies entered as relatively low-price and low-quality competitors to private pharmacies. While public pharmacies charge prices that are on average a third of those at private pharmacies, they enter at a single location per county, requiring travel distances that are on average three times larger than to private pharmacies. They also carry less product variety, have more restrictive operating hours and longer waiting times. In addition, the entry patterns of public pharmacies are consistent with an important role for politics. Entry was strongly concentrated in the months before local elections, as 86 percent of public pharmacies opened within the year preceding the elections.

To estimate the impacts of public pharmacies on economic and political outcomes, we combine a field experiment to study individual responses to the availability of public pharmacies, with quasi-experimental approaches to study aggregate outcomes and account for potential equilibrium effects. The field experiment consisted of an informational intervention to consumers, which

[1] Chile has relatively high drug prices and high out-of-pocket spending as a share of health expenditures when compared to other OECD countries (OECD, 2015).

we randomly provided during the weeks preceding the 2016 local elections in counties that had opened public pharmacies. The information covered the existence, location, and attractive and unattractive attributes of public pharmacies. We surveyed consumers before the intervention and two months after it, collecting data about drug shopping behavior and political participation. The quasi-experiment exploits the staggered entry of public pharmacies across counties. To support this design, we document that the timing of entry was unrelated to baseline differences or pre-trends in local market attributes. Moreover, anecdotal evidence suggests that the timing of entry of public pharmacies depended partly on unexpected delays in the bureaucratic procedure for obtaining the sanitary permits.

To understand the economic effects of public pharmacies, we first study individual behavior in the local pharmaceutical market. Using our field experiment, we estimate the impact of information about public pharmacies on consumer knowledge about them and shopping behavior across pharmacies. Our treatment increased knowledge about the availability of public pharmacies and their main differences with private pharmacies in terms of prices and quality. It also increased self-reported current and expected shopping intensity at public pharmacies. These effects were concentrated among consumers with household members with chronic conditions, who are exactly the set of consumers targeted by public pharmacies.

At the aggregate level, we find that the entry of public pharmacies impacted private sector market outcomes. We exploit drug-level data and the staggered entry of public pharmacies to estimate the impact on prices and sales in private pharmacies. A year and a half after opening, the average public pharmacy had shifted 4 percent of sales away from private pharmacies. The decrease in sales was concentrated among drugs targeted towards chronic conditions, which is consistent with our experimental evidence. We also find a *positive* and growing effect of public pharmacies on private sector prices: by the end of our sample period, the entry of public pharmacies had induced private pharmacies to increase their prices by 1.1 percent. We interpret this positive price effect as evidence that this low-price and low-quality public option generated market segmentation: private pharmacies responded to a shift of price-elastic consumers towards public pharmacies by increasing prices. We interpret the lack of a stronger shift in demand from private to public pharmacies in response to the large implied potential savings as coming from the lower quality of the latter. These results show that public pharmacies generated winners and losers as a consequence of its equilibrium effects.

The reduction in consumer drug expenditure generated by public pharmacies is substantially larger than their costs. We develop a simple accounting framework to implement this comparison. First, we estimate the cost of public pharmacies using data on municipal finances. We find that public pharmacies increased public spending on health services by more than the revenue derived from them. Second, we quantify the benefits that public pharmacies provide to consumers. Combining our estimates of economic effects with summary statistics on drug expenditures and prices, we find that introducing public pharmacies in every county would reduce yearly drug expenditure by 1.6 percent or US$55 million, which is 52 percent higher than the cost of the policy.[2]

Budget constraints and electoral incentives are crucial drivers of policy decisions (Besley and Case, 1995; Lizzeri and Persico, 2001; List and Sturm, 2006). Although we document that public pharmacies are relatively low cost and descriptive patterns suggest mayors expected political returns, their small negative impact on a large number of people suggests this policy might not be politically profitable. We find that the entry of public pharmacies increased the political support for incumbent mayors, particularly those who benefit the most from the policy. Exploiting our experiment, we show that awareness about the availability and attributes of a public pharmacy increased the likelihood of supporting the mayor by 6 percentage points in the local election. This effect is concentrated among households with members with chronic conditions. We combine these results with our estimates of economic effects and find that public pharmacies have a political return that is similar to that of cash transfers (Manacorda et al., 2011).

Individuals who were more exposed to public pharmacies were significantly more likely to vote for the incumbent mayor. To show this, we complement our experimental evidence by leveraging the quasi-random assignment of voters to booths, and administrative booth-level data covering almost 1.3 million individuals. We compare voting patterns of individuals who were affected by the public pharmacy with different intensity across counties that opened public pharmacies before and right after the 2016 election. The evidence confirms that political returns are higher among individuals who benefit the most from public pharmacies. A 1-kilometer increase in distance to the public pharmacy is associated with 5 percentage points fewer votes for the incumbent mayor who opened the pharmacy. Similarly, a 10-year increase in the average voter age in a given booth—which increases the likelihood of having a chronic condition and is associated with higher drug expenditure—is associated with a 1.2 percentage point higher vote share of the incumbent mayor. These voting patterns are consistent with our findings on economic effects, as both results are driven by households with chronic conditions.

Overall, our findings show that public firms in our context entered as low-price and low-quality competitors. We show that these firms caused market segmentation, which generated winners and losers: consumers who switched to public pharmacies benefited from lower prices, whereas those who stayed with private pharmacies lost from higher prices. Moreover, public pharmacies did not become a substantive financial burden, despite selling at remarkably lower prices than private pharmacies. This can be explained by two market failures in our setting: public pharmacies have more

[2] In addition to its economic effects, increased access to drugs could improve prescription adherence and thus health outcomes. Using data on avoidable hospitalizations and deaths, we find no evidence of such effects. This null result justifies our focus on reduced drug expenditure as a measure of benefits from public pharmacies.

bargaining power in the input market and thus hold a cost advantage relative to private pharmacies, and private pharmacies hold substantial market power in the retail market that translates into large markups over marginal costs. The extent to which these two conditions are met in other contexts informs the potential effectiveness of state-owned firms in them.

By analyzing the effects of public pharmacies, we inform the long-standing question of state versus private ownership of firms. A key aspect is the competitive effects that state-owned firms may induce on private firms. Most previous work has studied this form of competition in the context of large programs like public schools, (Epple and Romano, 1998; Hoxby, 2000; Dinerstein and Smith, 2018; Dinerstein et al., 2020) and health insurance (Duggan and Scott Morton, 2006; Curto et al., 2020), among others. Recent work has focused on the role of state-owned firms in local markets, either directly managed by the central government as in the case of milk stores in Mexico studied by Jiménez-Hernández and Seira (2020), or outsourced to the private sector as in Busso and Galiani (2019) and Banerjee et al. (2019) in the Dominican Republic and Indonesia, respectively. This work mostly finds that prices decrease upon increasing public competition. Our paper contributes to this literature by studying the effects of entry of locally managed public firms into local pharmaceutical markets, and by showing that public firms can induce potentially market segmentation and lead to an increase in prices by private firms.[3]

Our analysis of political support for incumbent mayors who opened public pharmacies is related to a large literature that studies if and how information about politicians and policies can shape political preferences. Previous research has studied the impact of information about the candidates in an election, incumbent policies, and the prevalence of corruption (e.g., Ferraz and Finan, 2008; Gerber et al., 2011; Chong et al., 2015; Kendall et al., 2015; Dias and Ferraz, 2019). Our experimental analysis differs from previous work by providing information about a specific policy directly to the people most likely to be affected by it and only a few weeks before the election. The focus on health relates our paper to recent work on the effects of the Medicaid Expansion on voter registration and turnout (Haselswerdt, 2017; Clinton and Sances, 2018; Baicker and Finkelstein, 2019). More generally, we contribute to the existing literature by providing novel evidence of political returns to the introduction of a public option in local markets.

Finally, this paper contributes to the literature analyzing policies that aim at increasing access to pharmaceuticals. Although access to affordable drugs is a first-order policy concern in low- and middle-income countries, which policies should regulators implement to achieve this goal is a highly debated issue (UN, 2010; Pinto et al., 2018). Recent work studies the effects of increased competition in the pharmaceutical retail market. Moura and Barros (2020) studies the price effects

[3]In this line, this paper also contributes to a broader literature studying how store entry affects local market outcomes including prices, sales, and market structure (see e.g., Basker, 2007; Hausman, 2007; Jia, 2008; Matsa, 2011; Atkin et al., 2018; Dinerstein and Falcao Bergquist, 2019; Arcidiacono et al., 2020).

of introducing competition in the market for OTC drugs, while Bennett and Yin (2019) studies the price and quality effects of the entry of retail chain pharmacies into a market dominated by low-quality firms. Other body of research focuses on the effects of different policies to lower drug prices, including price regulation (Mohapatra and Chatterjee, 2020), quality regulation (Atal et al., 2019) and public procurement (Dubois et al., 2019; Brugués, 2020). We provide novel evidence of how public competition in the retail pharmaceutical market affects equilibrium market outcomes.

The remainder of the paper is organized as follows. Section 2 describes the pharmaceutical market and public pharmacies, and section 3 describes the dataset. Section 4 introduces the key elements of our experimental and quasi-experimental research designs. Section 5 shows our findings for the effects of public pharmacies on shopping behavior and economic outcomes. Using these estimates, section 6 discusses the costs and benefits for consumers. Section 7 presents our results for the political effects and political returns of public pharmacies. Finally, section 8 concludes.

2 The public option in retail pharmaceutical markets

Before the introduction of public pharmacies, consumers could obtain pharmaceutical drugs by buying from private pharmacies or from public health care providers. According the 2016–2017 National Health Survey (*Encuesta Nacional de Salud*, ENS), as much as 40 percent of pharmaceuticals were purchased in the private retail sector, where there is limited insurance coverage. In fact, pharmaceuticals are the most important item of out-of-pocket health expenditures in the country (OECD, 2015; Benítez et al., 2018).[4] The private sector is highly deregulated, as there are no market structure regulations or price controls. The three largest chains account for around 80 percent of the market share (FNE, 2019), and stores are geographically clustered in relatively rich areas (MINECON, 2013). Margins for manufacturers and retailers were high during our period of study, at almost 50 percent and 40 percent respectively (FNE, 2019).

While private pharmacies purchase drugs from laboratories or from private wholesalers, the public sector uses an intermediary to aggregate the demand from the entire network of public providers to negotiate lower prices. This intermediary depends on the Ministry of Health and is called National Supply Center (*Central Nacional de Abastecimiento*, CENABAST). As part of the public sector, public pharmacies entered local markets with a cost advantage relative to private pharmacies by being able to purchased drugs through this public intermediary.

The rise of public pharmacies was preceded by a collusion scandal in the pharmaceutical industry in 2008, that involved the three largest pharmacy chains in the country (Alé, 2018). In a high

[4]There is no broad prescription drug insurance market in Chile. Instead, there are a few disjoint programs that mostly cover drugs in the public network or for a limited set of diseases.

profile antitrust case, the pharmacies were declared guilty. A left-wing mayor of a large county listened to public demands and opened the first public pharmacy in October of 2015.[5] Soon after, the popularity of the mayor boomed and dozens of other mayors from all political parties decided to inaugurate public pharmacies in the following months. By the end of 2018, 147 out of the 345 counties in the country were operating a public pharmacy. Figure 1 plots the number of counties with a public pharmacy over time and Figure A.1 display photos of a private and public pharmacy.

Public pharmacies offer products at lower prices than private pharmacies partly because they have access to the public intermediary. This intermediary receives orders from public healthcare institutions and negotiates with laboratories on their behalf. By aggregating demand from the public sector in a bidding process, the intermediary obtains lower prices than private pharmacies.[6] Without the intermediary, public institutions would have to buy products directly from laboratories at a potentially higher price. In practice, two thirds of the public pharmacies that were active by 2018 were purchasing drugs through the public intermediary. As we document in section 5.1, public pharmacy prices are on average around a third of private pharmacy prices. These differences are larger for branded than generic drugs, partly because the former are substantially more expensive in private pharmacies (Atal et al., 2019).

The potential beneficiaries of public pharmacies are determined by a combination of eligibility requirements, health conditions and location. First, the vast majority of public pharmacies require consumers to reside in the same county. A few impose milder constraints and require consumers to either live, study, or work in the county.[7] Second, public pharmacies offer mostly prescription drugs with a focus on drugs targeting chronic conditions. Hence, individuals with chronic conditions are more likely to benefit from public pharmacies. Third, the location of public pharmacies is relevant, as they are more likely to attract consumers that live nearby. Public pharmacies enter the market with a single location per county, whereas there are multiple private pharmacies in each market, which implies that for most of the population travel costs to public pharmacies are higher than to private pharmacies.

The increasing popularity of public pharmacies has been surrounded by economic and political controversies. On the economic side, there are two main criticisms. First, that public pharmacies may be financially unsustainable and could become a burden for local governments. This claim may have basis if counties relied on subsidies rather than on the public intermediary. Second, that

[5] The mayor and founder of the first public pharmacy quoted the Municipal Organic Law to back up his initiative, arguing that mayors must take care of citizens' health and the environment. According to the most recent political polls, he is among the leading presidential candidates for the 2021 election.

[6] Private pharmacies pay on average 70 percent more for the same drug than the public intermediary (FNE, 2019).

[7] Most of them are in the capital, where commuting across municipalities is more frequent. We consider this constraint when designing our field experiment by sampling consumers of private pharmacies located close to a public pharmacy. More details in section 4.1.

public pharmacies could be a form of unfair competition particularly towards non-chain private pharmacies, which accounted for 10 percent of the market, had limited buying power, and were not involved in the collusion scandal. These criticisms motivate part of our analysis, particularly the impact of public pharmacies on private sector outcomes and municipal finances.

On the political side, criticisms focused on the potential utilization of these pharmacies for electoral purposes. Their opening before the local election in October 23, 2016, in which incumbent mayors were running for reelection seemed far from a coincidence for many. Figure 1 shows that public pharmacy openings increased abruptly in the months before these elections and slowed down after it, which is hard to explain without resorting to a political argument. In fact, some politicians called public pharmacies "left-wing populism" (Publimetro, 2015), complained about their use "for political purposes" (La Tercera, 2016), and emphasized that they were "politically profitable" (El Mercurio, 2017). Whether pharmacies were used by mayors to get reelected or affected their evaluation are questions that motivate part of our empirical analysis.

3 Data

3.1 Public and private pharmacies

We collected the opening dates of public pharmacies. Openings span the period between October, 2015 and April, 2018. Figure 1 shows the number of openings per month and the evolution of the total number of public pharmacies operating over time. In addition to opening dates, we also geocoded the location of public pharmacies.

Regarding the supply of drugs by public pharmacies, we exploit detailed data on drug purchases for the 96 pharmacies that utilize the public intermediary. This data include the name, molecule, dosage, amount, and price of every drug transaction by public pharmacies in 2016–2018. Although these data only include purchase (instead of retail) prices, public pharmacies charge small or no markups. Unfortunately, we do not observe purchases from laboratories. Therefore, we cannot measure aggregate sales by public pharmacies and cannot estimate the impact of their entry on aggregate sales. Regardless, we use this data in section 5.1 to describe how prices, quantities and variety by public pharmacies compares to those in private pharmacies.

To measure outcomes for private pharmacies, we use data from IQVIA, a company that collects pharmaceutical market information worldwide. These data contain monthly local drug prices and sales for 2014–2018 collected from two sources. The four largest pharmacy chains, which account for more than 90 percent of market share, report retail prices and sales directly to IQVIA. Data for other pharmacies are collected from wholesalers.[8] IQVIA aggregates the data at the level of 66 local markets, which cover most of the country.[9] We restrict our attention to prescription drugs, which account for 93 percent of the drugs among the molecules we include in the analysis.

3.2 Local elections

In Chile, all mayors are elected simultaneously by a simple majority rule in elections held every four years and without term limits. To measure local political outcomes we use three administrative data sets from the Electoral Service (*Servicio Electoral*, SERVEL). The first contains county-level information about candidates, parties, coalitions, and votes by candidate in the 2012 and 2016 local elections. The 2012 election allows us to characterize the political equilibrium before the opening of public pharmacies. In particular, for each county and election we construct the number of competitors, the winning margin, and the vote share of the winner.

The second data source covers electoral results in the 2016 local elections at the booth-level, i.e. groups of 300 voters within a county. People vote in the county where they register, and booths are assigned using a quasi-random mechanism based on deaths and the goal of reaching 300 voters per booth. This algorithm implies that within a given county, the average observable characteristics of people across booths vary quasi-randomly. There are 42,000 booths in the data.

The third source of data is the electoral registry. For the more than 14 million people in the registry, we observe their self reported home address, gender, and age. As consumers usually purchase drugs in pharmacies close to their homes and they are more likely to have a chronic condition as they get older, we measure exposure to public pharmacies using home addresses and age. We sample booths and people from counties with a public pharmacy.[10] In the first step of the sampling, we randomly choose an average of 30 booths per county, with more (less) booths in larger (smaller) counties. In the second step, we randomly choose 30 individuals per booth. Then, we geocode the home addresses of the resulting 100,000 individuals in almost 4,000 booths. In the final step, we collapse the individual-level data to the booth-level and construct the following variables: percentage of women, average age, distance from voter homes to the public pharmacy

[8]IQVIA transforms wholesale prices to retail prices by adding a value-added tax of 19 percent and a retail margin of 30 percent. We adjust these prices in two ways. First, we adjust for inflation using the health CPI from the National Institute of Statistics (*Instituto Nacional de Estadística*, INE). Second, we compute prices per gram of the active ingredient to normalize them across presentations.

[9]Moreover, the data provide price and sales information at the product level for branded drugs, identifying the laboratory, dosage and presentation of each drug. For unbranded drugs, however, it only provides price and sales at the dosage and presentation level, aggregated across laboratories. This is irrelevant for our main analysis, as we focus on price indices and aggregate sales at the molecule level.

[10]We use a sample because we want to construct the home location of the average voter in a booth, geocoding is expensive, and we can estimate the location of the average voter using a random sample.

and to the county hall, and distance from the booth to the public pharmacy and the county hall.

4 Research design

We exploit two independent sources of variation in our analysis: the experimental variation induced by our informational intervention, and the timing of the entry of public pharmacies as a quasi-experiment. The former allows us to estimate consumer-level responses to the availability of public pharmacies. The latter approximates the ideal experiment of randomizing the entry of public pharmacies at the market level, which allows us to account for potential equilibrium effects.

4.1 The field experiment

We designed a field experiment to study whether information about public pharmacies affected consumers in the pharmaceutical market. The decision to provide information was based on a survey we conducted before the experiment, which revealed that consumers were uninformed along two dimensions. First, some households were unaware of the existence of a public pharmacy in their county. Second, even when households knew about the pharmacy, they were uninformed about the lower prices. The lack of information provides us with a unique opportunity to randomly expose consumers to public pharmacies using our experiment.

The treatment consisted of an informational flyer, displayed in Figures 3-A and 3-B. It provided information about the existence of a public pharmacy in the county, and stated that it offered lower prices and longer waiting times than private pharmacies. Additionally, it included its location, contact information, opening hours, and eligibility requirements. We delivered the flyer to consumers coming out of private pharmacies in the 20 counties with public pharmacies in Santiago, displayed in Figure A.2. The information was tailored to each county.

In terms of recruitment, enumerators approached consumers leaving a private pharmacy in each county and assessed their eligibility. Eligible participants were those who (i) lived and were registered to vote in the county, (ii) had purchased a prescription drug, and (iii) were not registered in the public pharmacy. Overall, 1,855 individuals were approached and 826 enrolled in the study. The baseline survey collected information on awareness of public pharmacies and their attributes, intention to vote for the incumbent mayor in the upcoming election, age, education, access to internet, among others. Once the survey was completed, participants were randomly assigned to treatment and control groups. The enumerator only learned the assignment of the individual after completing the survey. We implemented this survey between October 12 and 20, 2016, right before mayoral elections. Figure A.3 summarizes timeline of the events in the experiment.

Two months after the baseline survey, we conducted a follow-up survey to measure the same variables as in baseline. Additionally, we collected information about their relationship with the public pharmacy in their county. We implemented this survey by phone, and were able to complete the survey for 514 participants, almost two thirds of the sample.[11,12]

Table 1 compares both groups at baseline. Participants are on average 45 years old and 61 percent of them are female. More than 60 percent work and most use internet frequently. Half of the participants planned to vote for the incumbent and almost three out of four participated in the previous election. Slightly less than 70 percent knew about the existence of a public pharmacy. As expected, column 4 shows that almost all variables are balanced across groups. The exception is awareness of the public pharmacy, and we control for it in the analysis.

4.2 The entry of public pharmacies

In this section, we describe entry patterns of public pharmacies and discuss how they can be exploited to study their effects. We begin with a characterization of the counties that opened a public pharmacy. We then study the timing of entry of public pharmacies, and their location within the counties in which they opened. Our results show that counties that open public pharmacies differ systematically from those that do not, but that the timing of opening among those that open does not seem to be driven by observable county characteristics.

We start by comparing counties with and without public pharmacies. Columns 1, 4, and 5 in Table 2 show these results. The upper panels show that public pharmacies opened in dense high-income counties with more penetration of private health insurance, slightly better self-reported health, and with a private pharmaceutical market with more pharmacies, more sales and higher prices. In contrast, the lower panel shows few differences in political variables as measured by the previous local election of 2012. If anything, counties with a public pharmacy had more candidates, and were more likely to have a winner from the left-wing. In sum, counties with and without public pharmacies differ significantly in terms of their pharmaceutical market and socioeconomic characteristics but were relatively similar in their political characteristics.

The timing of public pharmacy openings is less associated with county characteristics. Columns 2, 3 and 6 in Table 2 compare counties that opened public pharmacies before and after the 2016

[11]Table A.3 evaluates the extent of attrition. Panel A shows that attrition is higher among younger participants, males, with higher support for the incumbent, less turnout in the last election, and less knowledge of the public pharmacy. While this changes the sample composition, it does not necessarily threatens the internal validity of the experiment. Panel B shows variables are balanced across experimental groups within the sample of non-attriters.

[12]In addition, this survey also verified the delivery of the treatment. Table A.2 shows that treated individuals acknowledged receiving information more often than those in the control group, and recalled public pharmacies being the core of the information content almost twice as often as the latter.

election. For this comparison, all differences are smaller in magnitude and almost none of them is statistically significant. To examine the timing of entry more systematically, we ranked all public pharmacies by their entry date, and estimated an ordered logit model for this ranking on all variables in Table 2. Pharmacies opening earlier entered counties with more population and are more likely to be run by left-wing mayors, but the timing of entry is otherwise uncorrelated with the characteristics of the pharmaceutical market, with socioeconomic attributes, and with electoral competition in the previous election. Instead, anecdotal evidence suggests that unexpected delays in sanitary permits explain why some pharmacies opened after the election. We rely on these results to exploit the comparison between counties that opened public pharmacies before and after the elections as a research design. For our analysis of political effects of public pharmacies, we further enrich the design with variation in the location of consumers relative to public pharmacies to measure differential exposure to the latter.

Finally, we document that mayors opened public pharmacies nearby existing private pharmacies, providing a unique opportunity to study the impact of the public option in an existing market. To describe their location choices, we geocoded all private pharmacies in the country and assigned them to geographic cells of 600×600 meters. We then estimated cross-sectional cell-level regressions using data from counties with a public pharmacy. The dependent variable is an indicator for a cell having a public pharmacy and the explanatory variables include the number of private pharmacies, the number of schools as a proxy of population, and county-level fixed effects. Table A.1 displays the results. The estimates reveal that public pharmacies opened in populated areas where private pharmacies were already operating. The maps in Figure 2 provide visual examples of the entry decision in the two largest urban areas in the country. These patterns are in stark contrast with the idea that public pharmacies entered in pharmacy deserts.[13]

5 Economic effects of public pharmacies

The introduction of public pharmacies provided consumers with an additional alternative for purchasing drugs. In this section, we study the implications of this policy for market outcomes. We start by describing their direct effects on prices, quality and shopping behavior. Then, we estimate their indirect effects on outcomes in the private market.

[13]A potential explanation for these entry location patterns comes from an interview we conducted with a mayor who opened a public pharmacy: his goal was to reach a large number of people.

5.1 Descriptive evidence on prices and quality

When public pharmacies opened, consumers in those markets had access to an additional alternative in their choice set which differed from available options along different dimensions. We describe this newly available option by using transaction-level data on the universe of purchases by public pharmacies from the public intermediary in 2016–2018, for the 96 counties that purchased drugs through it.

The most salient and advertised difference were drug prices. Using a set of exactly matched drugs that are sold in both public and private pharmacies, we study price differences across public and private pharmacies. In Figure 4-a, we show that almost all drugs are sold at lower prices in the former and that the relative price difference is, on average, between 64 percent and 68 percent depending on the margin that public pharmacies charge over purchase costs from the public intermediary. These large price differences suggest consumers should in principle substitute to public pharmacies in local markets in which they open.

Consumers trade-off lower prices with lower quality of public pharmacies. The fact that public pharmacies enter with a single store in each county implies that most consumers have multiple private pharmacies located closer to their homes than the public pharmacy. Using our data on voter home addresses and public and private pharmacy locations, we calculate distances between the former and every pharmacy in the county. The average (median) individual has 20 (12) private pharmacies located closer than the public pharmacy in their county. Figure 4-b shows that the distributions of distance to the closest private pharmacy and the public pharmacy differ markedly. In fact, the average distance to the closest private pharmacy is 0.6 kilometers, less than a third than that to the public pharmacy in their county. These facts imply that shopping at public pharmacies involve higher travel costs than shopping at private pharmacies. Moreover, public pharmacies offer a lower product variety. Figure 4-c shows that the average number of products per molecule-county is 2.2, and that 70 percent of molecule-counties offer three varieties or less, while the average number of varieties in private pharmacies is 15.2.[14] To the extent that consumers value product variety, these patterns imply that public pharmacies are less convenient on this dimension than private pharmacies. Longer waiting times and limited opening hours already mentioned in section 2 further exacerbate the relatively low quality of public pharmacies.

The relevance of public pharmacies has grown over time, reflecting that at least some consumers value lower drug prices relative to lower convenience enough as to switch to public pharmacies. Figure 4-d shows that their average market share across molecules and counties reached around 4 percent by the end of 2018. Of course, it is unclear whether sales by public pharmacies

[14] Relatedly, public pharmacies are more likely to offer only generic drugs or only branded drugs within a molecule: this is the case for 72 percent of molecule-counties at public pharmacies, but only for 36 percent at private pharmacies.

have decreased sales by private pharmacies or rather expanded market size. To inform this margin, we estimate the effects of public pharmacies on private pharmacy sales in section 5.3.

5.2 Experimental evidence on shopping behavior

Our experiment provided consumers with information on the availability of public pharmacies as an affordable alternative to purchase drugs. We now study whether consumers learned about the availability and attributes of public pharmacies, and whether knowing about them changed their shopping behavior in the short term. We estimate the equation:

$$y_i = \beta T_i + X_i'\gamma + \eta_{c(i)} + \varepsilon_i \tag{1}$$

where y_i is the outcome of interest; T_i indicates whether a consumer was treated; X_i is a vector of controls that includes the dependent variable at baseline along with consumer age, education, gender, and indicators for whether the consumer is covered by public insurance and whether a household member suffers a chronic condition; and $\eta_{c(i)}$ are county fixed effects. The coefficient β measures the average treatment effect of our informational intervention.

Information about public pharmacies made consumers more aware about their availability and attributes. Table 3-A displays these results. Columns 1 and 2 show that information increased awareness about the availability of the public pharmacy by 6 percentage points., from a baseline level of 82 percent. Moreover, columns 4 and 5 show that information shifted consumer perceptions about drug prices at public pharmacies, which is their most salient attribute. In particular, perceived public pharmacy prices decreased by 9 percent as a result of the intervention. We also find that perceived waiting time for receiving drugs at the public pharmacy increased, which is their main disadvantage relative to private pharmacies. In particular, perceived waiting time increased by 20 percent.[15] These results are consistent with consumers becoming aware of public pharmacies and their competitive advantages and disadvantages relative to private pharmacies as public pharmacies enter local markets.

Consumers also react to the intervention in terms of shopping behavior. Table 3-B displays results from linear probability models for the decision to enroll on the public pharmacy, the decision to purchase, and the plan to use the pharmacy in the future. Although the estimates are noisy, they are positive and economically meaningful. The results in column 2 indicate a 2 percentage points increase in enrollment on public pharmacies by treated households, almost a 30 percent

[15] We address concerns related to sample attrition by reporting bounds suggested by Lee (2009) in Table 3-A. In all cases, point estimates for both the lower and upper bound have the same sign as our estimated treatment effects. However, in some cases the point estimate of the bound is not statistically different from zero, implying that under relatively negative attrition scenarios our treatment effects are not distinguishable from zero.

increase relative to the mean of the control group. The results in column 5 imply a 2.3 percentage points increase in purchases in public pharmacies by treated households, more than an 80 percent increase relative to a baseline share of 2.8 percent in the control group. Finally, column 8 shows that our intervention increased the extent to which households plan to use the public pharmacy by 5 percentage points, as much as 10 percent relative to the baseline level for the control group.

Households with members that suffer chronic conditions react more strongly to the treatment. Columns 3, 6, and 9 study heterogeneity along this margin. All effects are larger for households with chronic conditions, although the differences are not statistically significant. Moreover, the treatment effects on effective and planned purchases are marginally statistically significant for consumers with chronic conditions. Consumers with chronic conditions are a group more likely to periodically shop for drugs and, thus, the group for which short term effects are more likely to be detectable. Moreover, in many cases public pharmacies prioritize the provision of drugs treating chronic conditions, thus the information in our intervention may be less relevant for consumers without any household member with a chronic condition. Treatment effects on consumers without a household member with a chronic condition are indeed close to zero across outcomes.[16]

These results suggest that as public pharmacies enter local markets, consumers become aware of their entry, their relative advantages in terms of lower prices, and their relative disadvantages in terms of convenience. Moreover, our findings suggest that consumers value the availability of public pharmacies and some, particularly those affected by a chronic condition, substitute towards public pharmacies to take advantage of their lower drug prices.

5.3 Equilibrium effects on prices and sales by private pharmacies

Public pharmacies may induce consumers to substitute away from private pharmacies. Moreover, the competitive pressure from public pharmacies may induce private pharmacies to adjust prices. In this section, we estimate the effects of the entry of public pharmacies on private pharmacies.

5.3.1 Event study evidence

We start by exploiting the staggered entry of public pharmacies in an event study framework. For this analysis, we use IQVIA data on drug prices and sales across local markets. A challenge for combining data on entry of public pharmacies with data from IQVIA is that the level of geographic aggregation of the latter is in some cases larger than counties, which is the level at which public

[16]We report Lee bounds in Table 3-B to address concerns about attrition. We find that point estimates for both the lower and upper bound have for all outcomes have the same sign as our estimated treatment effects, although some of those bounds are not statistically different from zero.

pharmacies operate. To tackle this issue, we estimate a stacked event study regression.[17] Whenever a location has more than one event, we create as many copies of the data as the number of events. We stack the copies in a dataset and use the entry of public pharmacies to all counties within a location as events. Figure A.5 shows the distribution of the number of events per local market.

The main specification we estimate takes the following form:

$$y_{mlgt} = \sum_{k=-12}^{15} \beta_k D^k_{lgt} + \lambda_{mt} + \theta_{mlg} + \varepsilon_{mlgt} \tag{2}$$

where g indexes entry events within a local market. The dependent variable y_{mlgt} is either logged drug prices or logged drug sales for molecule m in local market l in month t.[18] Our interest is on the coefficients β_k on the dummies $D^k_{lgt} = 1\{t = e_{lg} + k\}$, which indicate whether a month t is exactly k months after event time e_{lg} for event g in local market l. We normalize $\beta_{k=-1} = 0$, so we interpret all coefficients β_k as the effect of a public pharmacy opening on the dependent variable exactly k months after its entry. The specification also includes molecule-month fixed effects λ_{mt} to account for time varying unobservables at the level of molecules, and molecule-location-event fixed effects θ_{mlg} to account for persistent differences in market conditions across local markets. Standard errors are clustered at the molecule-location level.[19]

The entry of public pharmacies had meaningful effects on private pharmacies. Figures 5-a and 5-b present the results for sales and prices respectively. Drug sales by private pharmacies decrease after a public pharmacy enters a location. Our estimates imply that 15 months after the entry of a public pharmacy, private pharmacies in that market sell around 3 percent less. Furthermore, drug prices in private pharmacies increase by 1 percent 15 months after the entry of a public pharmacy.[20] Both effects increase over time, suggesting that public pharmacies evolve in terms of

[17]This approach has been adopted by recent work estimating event study analysis in settings with multiple events per unit (see e.g., Lafortune et al. 2018; Cengiz et al. 2019).

[18]We define the market-level price as the share-weighted average of log prices:

$$\hat{P}_{mlt} = \sum_{i \in \mathcal{I}_{ml}} w_{il0} P_{ilt}$$

where $\mathcal{I}_{ml}$, is the set of drugs of molecule m in local market l, P_{ilt} is the log price per gram of product i in period t and location l, and w_{il0} denotes the share of sales of drug i in location l in 2014. Because these weights are constant, changes in the index are driven by changes in prices and not by changes in market shares or in the market structure. This price index has been previously used in the literature that studies retail pricing (e.g., Atal et al., 2019). For sales, we use the residuals from the projection of the outcome variable on month-of-the-year fixed effects by molecule-location to account for seasonality that is specific to sales in some locations (e.g., due to tourism in summer).

[19]We use a balanced sample of locations in event time, and include never-treated locations to pin down the linear component of pre-trends (Borusyak and Jaravel, 2018). Moreover, we fully saturate the model, and report results for event dummies 12 months before and 15 months after the event, for which all locations are balanced in event time.

[20]There is limited cross-sectional variation in prices across locations, in line with recent evidence from other

enrolling more consumers and possibly improving their product offerings and convenience.

The main threat to the identification of the effect of public pharmacies is reverse causality. Unobserved determinants of sales and prices in the private sector may drive the entry of public pharmacies. In that case, β_k would confound the causal effect of public pharmacies on private market outcomes with trends in outcomes that cause the entry of public pharmacies.[21] Reassuringly, the lack of pre-trends in both sales and prices leading to the entry of public pharmacies suggests that reverse causality and strategic considerations do not play a significant role in our setting.[22]

We provide results for alternative specifications in Appendix A.1. We consider a standard event study regression, where we define unique entry events per location. Since there is no obvious way to define an event in our setting, we provide evidence for two alternative definitions of the event: entry as the first public pharmacy to enter a local market and entry as the largest county to enter a local market. In both cases, results are quantitatively similar to those from our main specification.

5.3.2 Main results

We obtain our main results by estimating a more parametric version of equation (2), where the treatment variable is an index of public pharmacy intensity, PPI_{lt}. This variable measures the share of population in local market l that lives in counties with a public pharmacy in month t. The advantage of this variable is that it exploits all the variation in the timing of entry of public pharmacies and appropriately scales it at the level of at which market outcomes are measured by accounting for the heterogeneity in market size across markets. The estimating equation is:

$$y_{mlt} = \beta PPI_{lt} + \lambda_{mt} + \theta_{ml} + \varepsilon_{mlt} \tag{3}$$

where the interpretation of β is as the effect of all counties in location l opening a public pharmacy.

The main results are similar to those in the event study framework, as shown by Table 4. The entry of public pharmacies decreases drug sales by private pharmacies by 4 percent and increases

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contexts (Adams and Williams, 2019; DellaVigna and Gentzkow, 2019). This limits the extent to which we expect to find price effects. Moreover, our research design is only able to identify price effects stemming from variation across local markets, and thus any market-wide price effects across locations are not captured by our empirical strategy.

[21] Strategic entry is an identification threat for reduced form models for the effects of firm entry as equation (2), but it is not a relevant concern in our context. Public pharmacies' business model differs from private pharmacies', as they do not operate as for-profit businesses. Furthermore, some public pharmacies are subsidized by local governments.

[22] As an additional piece of supporting evidence, in column 7 of Table 2 we study the order of entry of public pharmacies using an ordered logit regression of entry on market and political covariates. The results show that the timing of entry is uncorrelated with covariates associated to the supply and demand of drugs.

drug prices by private pharmacies by 1.1 percent.[23,24,25]

The effects of public pharmacies on private pharmacy sales are stronger for molecules associated with chronic conditions. Column 3 in Table 4 shows a decrease in sales of 5.4 percent for such molecules, and a decrease of only of 2 percent for molecules associated with non-chronic conditions. This finding is consistent with public pharmacies mostly focusing on drugs related to chronic conditions. Moreover, it is consistent with our experimental evidence showing that households with members with chronic conditions react more strongly to the availability of public pharmacies in terms of shopping behavior. For prices, column 6 in Table 4 shows, in contrast, that the effect is somewhat larger for molecules associated with chronic conditions.

5.3.3 Discussion

The entry of public pharmacies had equilibrium effects on private pharmacies. As expected due to lower prices offered by public pharmacies, some consumers substituted away from private pharmacies and drug sales in the latter decreased. While increased competition could have induced private pharmacies to reduce drug prices, we find that private pharmacies instead increased prices. This response is consistent with consumers sorting across public and private pharmacies on the basis of their price elasticity. Price-elastic consumers decide to switch to public pharmacies, whereas less price-elastic consumers do not value lower prices enough as to compensate for lower quality and do not switch. Private pharmacies internalize this change in their pool of consumers and respond to such segmentation and a more inelastic residual demand by increasing drug prices. This mechanism for price increases in response to rival entry is formalized by Chen and Riordan (2008).[26]

The sales response to the entry of public pharmacies may seem small given the magnitude of the price differences between public and private pharmacies. Our interpretation is that product differentiation plays a role in mediating this response. As documented above, public pharmacies are

[23]The event study results and these results are quantitatively similar, because entry events are not too dispersed over time. Thus, event study coefficients for periods far enough after the first entry event actually capture the effect of most if not all public pharmacies entering a location. For completeness, we report results of equation (3) using exposure to the first public pharmacy only in Table A.5, for which results are almost the same.

[24]We provide additional results on price effects in Appendix A.2. In particular, we provide results from a decomposition developed by Atal et al. (2019) for the effects of public pharmacies on average paid prices for drugs in molecule-location. Average paid prices increased by 1.7 percent following the entry of public pharmacies, such that price changes by private pharmacies were indeed the main driver of such change. The remainder of the increase in average paid prices is driven mostly by entry of relatively expensive drugs after the entry of public pharmacies.

[25]An additional margin of response for private pharmacies would be to adjust product variety. We estimate equation (3) using the number of varieties offered as dependent variable, and find no evidence of responses along that margin.

[26]Caves et al. (1991) and Frank and Salkever (1997) document a similar pattern of market segmentation in pharmaceuticals, where innovator drugs that become off-patent do not decrease but rather *increase* their prices after generic entry. This fact is known in the literature focused on competition in pharmaceutical markets as the “generic paradox”.

less convenient than private pharmacies in terms of waiting times, opening hours, product variety, and travel distance. The lack of a stronger response suggests that a sizable share of consumers value those attributes enough as to not substitute towards public pharmacies on the basis of lower prices. Higher quality public pharmacies would have likely led to stronger equilibrium responses. Second, our event study results in Figure 5 show that both quantity and price effects increase over time, suggesting that the full effects once the market settles on a new equilibrium may be larger.

The substitution away from private pharmacies that we estimate is consistent with the findings in related work by Busso and Galiani (2019) and Jiménez-Hernández and Seira (2020) in different contexts. However, they find a price decrease among private firms, as opposed to a price increase. Our results highlight that the price effects of public competition will depend on the underlying consumer preferences and firm attributes.

6 The benefits and costs of public pharmacies

Our results so far show that public pharmacies entered the market as a low price and low quality alternative to private pharmacies, and induced competitive responses by private pharmacies. In this section, we discuss the relative efficiency of public firms. First, we estimate the cost of pharmacies, by exploiting data on municipal finance to study the effects of introducing a public pharmacies on spending and revenue on health and non-health services. Second, we assess whether public pharmacies have any health effects on consumers as measured by avoidable hospitalizations. Finally, we develop a simple framework that exploits our estimates of economic effects of public pharmacies in section 5 to estimate how consumer drug expenditure decreases as a result of public pharmacies, and compare it to our cost estimates.

6.1 Municipal finance and the cost of public pharmacies

Given that public pharmacies were created by local governments that manage multiple other local services, it is important to understand whether these are economically sustainable or represent a financial burden that may crowd-out other services. To study this margin, we exploit administrative data from municipal finances to estimate the financial impacts of public pharmacies.[27]

[27]The data comes from the National System of Municipal Information (*Sistema Nacional de Información Municipal*, SINIM). Counties spend resources in transportation, public education, public health, culture, and sports, among others (Law 18,695). Approximately 90 percent of their budget comes from county revenues (property and vehicle tax receipts) and the rest of resources correspond to monetary transfers from the central government.

For this analysis, we estimate the following regression:

$$y_{ct} = \delta PP_{ct} + \theta_c + \lambda_t + \varepsilon_{ct} \tag{4}$$

where y_{ct} is a financial outcome in county c and year t (e.g., spending in health services), PP_{ct} indicates the period after the entry of a public pharmacy in county c. The specification includes county and year fixed effects. In terms of data, we observe annual county spending and revenue for 2013–2019. Both spending and revenue have subcategories that we aggregate into health and non-health categories. To ease the comparison across counties, we use the log spending and revenue per capita as dependent variables in this analysis.[28]

Table 5 presents these results. These estimates deliver two main results. First, the entry of public pharmacies are associated with an increase of 5.1 percent in health spending in column 1, that is somewhat compensated by an increase in health revenue of 3.8 percent in column 2. The difference between these effects is statistically significant, with a p-value of 0.066. Second, we do not find strong evidence suggesting that public pharmacies affect non-health services in columns 3 and 4. While our point estimates imply that spending in non-health services decreases more than its revenue, those coefficients are not statistically significant. In terms of overall municipal finance, our point estimates in columns 5 ans 6 imply that spending increases more than revenue, although those coefficients are again not statistically significant. Put together, this evidence suggests that the higher deficit in health services induced, if any, only a slight amount of crowd out of other municipal services and a small increase in the overall municipal deficit.[29]

These estimates allow us to compute the average cost of introducing a public pharmacy. Public pharmacy profits depend on the markup they charge on drugs, if any, and any initial investment and operation costs it incurs. The fact that public pharmacies induce a deficit implies they set prices below average cost. The average spending and revenue per capita in health services are \$164.7 and \$163.1. The average county in the country has a population of 52,325. Combining these basic statistics with our estimates in columns 1 and 2 of Table 5, we calculate that the annual loss of the public pharmacy in the average county is \$115,037.[30] In the next sections, we compare this cost estimate with the estimated benefits of public pharmacies for consumers.

[28]Some counties adding up to 7 percent of the sample do not report the breakdown of their accounts for health and non-health services. To have a uniform sample across dependent variables, we drop those observations.

[29]Figure A.11 displays the corresponding event study estimates for this specification, which provide reassuring evidence regarding the trends in these outcomes leading to the entry of public pharmacies.

[30]Articles from local newspapers that disclose public pharmacy non-drug costs place the yearly cost of running them at between \$85,000 and \$125,000, in line with our estimates (see e.g., Araucanía Cuenta 2016; El Austral 2017; Clave9 2017; Diario Concepción 2017).

6.2 Lack of health effects of public pharmacies

Increased access to pharmaceutical drugs could benefit individuals through health improvements. Such effects could operate through improved adherence to prescription drugs for individuals with chronic diseases due to lower prices and increased access (Cutler and Everett, 2010). However, in our setting we do not observe individual level prescriptions and drug purchases. Instead, we focus on avoidable hospitalizations associated with chronic diseases, which would have likely not occurred under appropriate disease management. This variable has been employed previously in the literature (e.g., Layton et al., 2019). The fact that public pharmacies were oriented towards individuals with chronic diseases makes this variable particularly suitable. We would interpret a decrease in avoidable hospitalizations after the entry of a public pharmacy as a signal that the pharmacy increased drug access and, in consequence, adherence by individuals with chronic diseases.

For this analysis, we estimate equation (4) using hospitalizations as the dependent variable. We exploit data on monthly hospitalizations for 2013–2018 from the Ministry of Health (DEIS, 2019), which cover number of hospitalizations, days of hospitalization, number of surgeries, and number of deaths per diagnosis across all hospitals in the country. The number of hospitalizations captures only the volume of these events, whereas hospitalization days, surgeries, and deaths capture their severity. To focus on the subset of diagnoses for which hospitalizations are considered avoidable, we follow the Prevention Quality Indicators in AHRQ (2019), which lists all ICD-10 diagnosis codes for admissions associated with asthma, chronic obstructive pulmonary disease, diabetes, and hypertension. We restrict our sample of hospitalizations for this analysis to these diagnoses. We normalize these variables by population and measure them per 100,000 inhabitants.

Our estimates provide no evidence that public pharmacies improved health outcomes in the short run, at least as measured by avoidable hospitalizations. Table 6 displays these results. For each outcome, we first show results for all individuals and then for individuals under public insurance (*Fondo Nacional de Salud*, FONASA), which are on average of lower income and more likely to benefit from the public pharmacy. Across all outcomes and samples, we find no statistically significant effect of the entry of a public pharmacy to a local market. That said, our estimates are not precise enough as to rule out effects that could be quantitatively meaningful. In particular, our estimates can reject at the 5 percent level reductions of 1.07 hospitalizations, 9.68 hospitalization days, 0.13 surgeries, and 0.03 deaths per 100,000 inhabitants as a result of the entry of public pharmacies, which are equivalent to reductions of 4–7 percent in these outcomes relative to their baseline levels.[31]

[31] Figure A.12 shows results from an event study version of equation (4). For all outcomes and samples, we again find no evidence that public pharmacies affected health outcomes. Reassuringly, these results show a lack of differential trends across counties leading to the entry of public pharmacies, which provides evidence against reverse causality.

Overall, our interpretation of these results is that public pharmacies did not affect access to drugs in a magnitude such that it improved adherence enough as to reduce avoidable hospitalizations. In this line, while we cannot measure effects on aggregate drug consumption, these results suggest that if public pharmacies had any market creation effect, it was small, and that most of their effects was through business stealing from private pharmacies.

6.3 Comparing costs and benefits

In this section, we exploit our previous results to compare the benefits and costs of public pharmacies. The calculation of benefits from public pharmacies focuses on the benefits from drug lower prices, given that we find no evidence of health effects. In this line, we develop a simple accounting framework to estimate effects on consumer expenditure by combining our results on economic effects from section 5 with basic statistics from the market.

Let r denote private pharmacies and u denote the public pharmacy. Moreover, let $t = 0$ indicate the period before the entry of the public pharmacy, and $t = 1$ the period after its entry. Using this notation, total consumer expenditure in period t is given by $e_t = M_t(s_t^r p_t^r + s_t^u p_t^u)$, where M_t is the amount of drugs consumers need; s_t^r and s_t^u are market shares of the private and the public pharmacy respectively; and p_t^r and p_t^u are composite drug prices at each of them. We impose two assumptions. First, we assume that the market size remains constant over time, such that $M_t = M$ for $t = 0, 1$. Second, and given we are unable to estimate aggregate effects on drug quantity with the available data, we rule out such effects and impose $s_t^r + s_t^u = 1$ for $t = 0, 1$.

The object of interest is the change in drug expenditure upon the entry of the public pharmacy:

$$\Delta e = M(s_1^r p_1^r + s_1^u p_1^u) - M(s_0^r p_0^r + s_0^u p_0^u)$$

which we can rearrange as follows. First, note that naturally $s_0^r = 1$ and $s_0^u = 0$. Second, we use our estimates of effects on private pharmacies from section 5.3 to express sales and prices by private pharmacies after the entry of the public pharmacy as $s_r^1 = (1 - \beta_s)s_0^r$ and $p_r^1 = (1 + \beta_p)p_0^r$, respectively. Finally, we use results from section 5.1 on price differences between public and private pharmacies to express public pharmacy prices as $p_u^1 = \phi_1^u p_r^1$, where ϕ_1^r is the average discount that public pharmacies offer relative to private pharmacies. After replacing and rearranging, we get:

$$\Delta e = \underbrace{Mp_0^r}_{\substack{\text{Baseline}\\ \text{expenditure}}} \times \; [\underbrace{(1 - \beta_s)(1 + \beta_p) - 1}_{\substack{\Delta\text{ expenditure}\\ \text{in private pharmacies}}} + \underbrace{\beta_s \phi_1^r (1 + \beta_p)}_{\substack{\Delta\text{ expenditure}\\ \text{in public pharmacy}}}]$$

To measure the change in drug expenditure, we proceed as follows. We measure baseline expenditure using data from the 2016 National Household Spending Survey (*Encuesta de Presupuestos Familiares* EPF) stating that the average yearly drug expenditure was \$213.4. Furthermore, our estimates from section 5.3 imply that $\beta_s = 0.040$ and $\beta_p = 0.011$. Finally, we know from section 5.1 that public pharmacies set prices at an average of $\phi_1^u = 0.34$ of private pharmacy prices.

The average consumer saves US\$3.3 per year according to these estimates. This average masks considerable heterogeneity, as those who stayed at private pharmacies increased in their expenditure by \$2.3, whereas those who switched to the public pharmacy reduced their expenditure by \$140. A population of particular interest is that of consumers with chronic diseases, who are the main target of public pharmacies and account for 22 percent of the population according to the 2016–2017 ENS. Our estimates imply that these consumers decreased their yearly expenditure by an average of \$22.3 per year. Among them, those who stay with the private pharmacy increase their expenditure by \$6.5, whereas those who switch decrease it by \$537.8 per year. Adding up across consumers, these estimates imply that consumers in the average county decrease their overall spending by \$175,181 per year. Finally, if every county in the country adopted a public pharmacy, the aggregate reduction in spending would be of \$60,262,544 per year, which is equivalent to 1.6 percent of total drug expenditure according to the EPF.

Our estimates imply that consumer benefits in terms of reduced drug expenditure on inframarginal units are 52 percent higher than the cost of public pharmacies. Public pharmacies achieve reductions in consumer expenditure higher than their costs because of two reasons: private pharmacies hold a cost advantage relative to private pharmacies when purchasing from laboratories, and private pharmacies hold substantial market power in the retail market (FNE, 2019). Public pharmacies thus deal with two salient market failures in this industry. Because of this, the introduction of a public firm likely performs better than an alternative policy of subsidizing drug purchases. In this simple framework, the cost of a subsidy is the reduction in drug expenditure, and is thus higher than that of the public pharmacy according to our estimates. This is because subsidies have the ability to reduce drug expenditure, but do not deal with market power in the private market, and therefore must incur a higher cost to achieve the same effects as the public pharmacy.[32]

Of course, this is not a full welfare analysis and has clear limitations. On the one hand, we do not account for potential market expansion effects, which imply we may underestimate the benefits of public pharmacies. On the other hand, we do not account for the value consumers may place on the relative convenience of private and public pharmacies. The fact that relatively few consumers switch despite the large potential savings for switchers suggests that the valuation of these non-price pharmacy attributes is large. A richer model of consumer demand and pharmacy pricing is needed to develop such analysis.

[32]Enriching the framework to account for aggregate effects would exacerbate the extent to which public firms would outperform subsidies, as subsidies would in that case induce an additional deadweight loss.

7 Political effects of public pharmacies

Budget constraints and electoral incentives are crucial drivers of policy decisions (Besley and Case, 1995; Lizzeri and Persico, 2001; List and Sturm, 2006). Although public pharmacies are relatively low cost and Figure 1 suggests mayors expected political returns, their small negative impact on a large number of people suggests this policy might not be politically profitable. The existence of political returns is important because it informs the likelihood of policymakers adopting this policy elsewhere. In this section, we show that voters rewarded mayors for opening public pharmacies, particularly those who were more likely to use their services.

7.1 Experimental evidence on consumer political preferences

We exploit experimental variation from our informational intervention along with self reported voting behavior to estimate the causal effect of awareness of public pharmacies among consumers in the pharmaceutical market on political support for the incumbent. Our baseline survey asked about the intention to vote for the mayor in the upcoming local election. Similarly, our follow-up survey asked whether the individual actually voted in the election. In the few counties where the incumbent did not run for reelection, we asked about the intention to support the mayor's candidate, as measured by the candidate running under the the same political party of the incumbent mayor.

Table 7 presents results from estimating equation (1) for political outcomes. Columns 1 and 4 study self-reported voting voting behavior. As much as 26–28 percent of the control groups reported to vote for the incumbent, which increases by approximately 6 percentage points for the treatment group. While these point estimates are large in magnitude, they are not statistically significant at conventional levels, with p-values of 0.21 and 0.12. To increase the precision of the analysis, columns 2 and 5 control for the intention to vote for the mayor at baseline along other covariates, and include county fixed effects. Treatment effects using this specification remain similar in magnitude but indeed become more precise, with p-values of 0.06 and 0.11.[33]

Effects on voting behavior are concentrated among individuals from households with members with chronic conditions. Columns 3 and 6 explore these patterns of heterogeneity. Households with someone with a chronic condition report having voted 8 percentage points more for the incumbent, larger than the 2–7 percentage points higher vote share among treated households without a chronic condition. Although the small sample prevent us from rejecting the null of a similar impact across these groups, the result is consistent with the the hypothesis that people most affected by the policy are more likely to support the incumbent.

[33]To account for the effects of attrition, Table 7 presents Lee bounds. The lower bound is positive but not statistically significant and the upper bound is positive and statistically significant across the three outcomes we study.

Finally, columns 7–9 repeat the previous estimations but now using as dependent variable an indicator that takes the value of one if the person voted at the election. The estimates reveal a positive impact on the probability of turning out to vote, with point estimates similar in magnitude to previous estimates, although in this case none is statistically significant at conventional levels. All in all, these results suggest that the awareness about public pharmacies and their characteristics increased consumers support for the incumbent mayor.[34]

To put these effects in context, we calculate the implied persuasion rate of public pharmacies (Enikolopov et al., 2011). In our case, the persuasion rate corresponds to the percentage of people who were exposed to (or informed about) the pharmacy and because of it were persuaded to vote for the incumbent mayor. In the absence of the pharmacy they would have voted for the challenger or not voted at all. This persuasion rate is a function of our estimates and we calculate it to be around 4 percent. We provide more details about this calculation in Appendix B. The persuasion of public pharmacies is lower than the persuasion of an independent television channel in Russia (Enikolopov et al., 2011) and political campaigns in dictatorship in Chile (González and Prem, 2018), but similar to the persuasion of Fox News in the U.S (DellaVigna and Kaplan, 2007).[35] Moreover, mayors in 20 of the 147 municipalities with public pharmacies won by less than 4 percentage points in the 2016 elections, which suggests this effect is of sizeable economic magnitude.

7.2 Quasi-experimental evidence on voting patterns

Public pharmacies are more likely to be used by people with chronic conditions, high drug expenditure, and that live closer to them. Are these people rewarding the mayor relatively more than others? To answer this question, we use booth-level voting data in the 2016 election from counties with public pharmacies. We use a differences-in-differences design that exploits two sources of variation. First, we exploit the quasi-random assignment of citizens to booths within counties to construct measures of exposure to public pharmacies. In particular, we focus on booth-level variation in the proximity of voters' homes to the public pharmacy and voters' age as measures of geographic and health-related exposure.[36] Second, we exploit variation in the opening date of phar-

[34]A potential concern with Table 8 is the possibility that mayors incentivized the use of public pharmacies before the election to gain votes. We used two monitoring strategies and conclude that this is unlikely to be a concern. Panel (a) in Figure A.4 shows that the number of consumers per hour in public pharmacies was similar around election day. Panel (b) shows that political propaganda, as visualized by enumerators, was similar in public and private pharmacies.

[35]Figure A.9 provides more details about these comparisons. DellaVigna and Gentzkow (2010) provide an early review of the empirical evidence on persuasion rates.

[36]We use voter age as a proxy for having a chronic disease and for having high drug expenditure. Figure A.10-a shows that the share of individuals that use drugs to treat chronic diseases increases rapidly with age, whereas Figure A.10-b shows the same for drug expenditure. As expected, Figure A.10-c shows that the distribution of voters' age across booths in counties with pharmacies that opened before and after the election is similar.

macies. Some opened *before* the elections and some began operating *after*. Anecdotal evidence suggests that pharmacies opening after the elections were planning to open before but experienced delays in acquiring the required sanitary permit. Using voting booths in counties where a public pharmacy opened after the election allows us to control for the geographic sorting of voters with different political preferences and the impact of age on voting patterns.

Using 3,855 booths from 141 counties with public pharmacies, which correspond to almost 1.3 million voters, we estimate the following equation:

$$v_i = \beta_D D_i O_{c(i)} + \beta_X X_i O_{c(i)} + \gamma_D D_i + \gamma_X X_i + \phi_{c(i)} + \epsilon_i \tag{5}$$

where v_i is a voting outcome in booth i in county $c(i)$. We focus on two outcomes, vote share for the incumbent and turnout. The variable of interest in the vector D_i is the log average distance from the home of voters in booth i to the public pharmacy operating in county $c(i)$. This vector also includes the log distance from voting booth i to the public pharmacy in $c(i)$ and the log distance from voter homes in booth i to the city hall in $c(i)$. The dummy $O_{c(i)}$ indicates counties where public pharmacies opened before the 2016 elections. The vector X_i includes the characteristics of voters in booth i, namely the log average age and share of female voters. Finally, $\phi_{c(i)}$ is a set of county fixed effects, and ϵ_i is an error term. The parameters of interest are β_D and β_X, which measure the differential voting behavior of individuals who lived close to a public pharmacy that opened before the elections—those who were more exposed geographically—, and of relatively old individuals in counties where the public pharmacy opened before—those who were more exposed in terms of having higher potential benefits from better options in the local pharmaceutical market. This strategy exploits the differential treatment intensity that public pharmacies had on different types of people within the county.

Exposure to public pharmacies affects voting behavior and increases support for the incumbent. Table 8 presents estimates of equation (5). Column 1 shows that voters living closer to a public pharmacy display a higher vote share for the local incumbent than those living farther. In particular, the estimate in column 1 implies that a 1-kilometer increase in the distance to the public pharmacy is associated with 5 percentage points fewer votes for the incumbent coalition, an increase of 10 percent over the sample average. Column 2 shows that this effect is similar when we restrict attention to the majority of counties in which the incumbent mayor decided to run for reelection. Similarly, booths with relatively old voters were more likely to support the mayor when the pharmacy opened before the election. Results in columns 1 and 2 imply that a 10-year increase in the average age of voters in a booth (around 1 standard deviation in the average age distribution) is associated with a higher vote share for the incumbent of 1.2 percentage point. Finally, column 3 shows that there is no statistically significant relationship between these variables and turnout, defined as valid votes over registered voters in the booth. These estimates imply that a higher exposure to the public pharmacy shifted voting towards the incumbent mayor, and are consistent with our experimental estimates.

These results suggest that public pharmacies increased the vote share of incumbent mayors. Both strategies approximate the ideal experiment in which pharmacies are randomly allocated across counties. However, a threat to both is the potential for the comparison group to be somewhat treated. In the field experiment, individuals in the control group had imperfect information about public pharmacies, which likely reduces the causal impact of information when compared to a scenario with a perfectly uninformed control group. Similarly, in the quasi-experimental design voters could have rewarded the mayor for the (expected) future opening of the pharmacy. Both concerns imply that our estimates are a lower bound for the political effects of public pharmacies.

7.3 The political returns of public pharmacies

We combine our results on effects in with those on consumer savings from section 6.3 to estimate the political returns of public pharmacies. The experimental results from section 7.1 imply that introducing a public pharmacy increases the number of votes for the incumbent by 1,055, relative to an average of 16,105 total votes across counties in the 2012 local election. Our estimates of effects on drug expenditure imply that the incumbent obtains 1 additional vote per $166 of yearly consumer savings.

To put the political returns of public pharmacies in perspective, we compare these to the impact of cash transfers. We consider the monthly savings of consumers who switch to public pharmacies and focus on consumers with chronic conditions. The average individual with this attribute gets monthly savings of $44.8. These "transfers" increased the political support of the incumbent mayor by 8.1 percentage points. For reference, Manacorda et al. (2011) find that a targeted monthly transfer of $70 increased the political support of the incumbent government by 11 percentage points in Uruguay. Assuming linearity, we calculate that a cash transfer of $70 targeted to consumers with a chronic disease would increase support for the incumbent by 12.6 percentage points. Thus, we estimate a political return that is similar to that of targeted cash transfers.

8 Conclusion

State-owned firms compete with the private sector in a variety of markets. The costs and benefits of such competition are both economic and political, and have been difficult to evaluate empirically in the same context. In this paper, we leverage the decentralized entry of public firms to a fully deregulated private market of pharmaceutical retailers. We show that the public option emerged as a low-price and low-quality option and affected the shopping behavior of local consumers, generating market segmentation and higher prices in the private sector. Although public pharmacies created winners and losers within local markets, overall consumer savings outweighed the costs of public pharmacies, and mayors were politically rewarded for opening the pharmacies.

While our study focuses on a particular form of public-private competition, it provides general lessons. First, the public option triggers general equilibrium effects through consumer demand responses and, as a consequence, price responses by private firms. These equilibrium effects can make some consumers worse off. In our context, these consumers are those with a high willingness to pay for service quality relative to drug prices. Second, our analysis highlights that public competition may be effective at reducing consumer expenditure. In industries with substantial market power in the input and retail markets, retail prices are set at markups over marginal costs. Whenever state-owned firms have higher bargaining power in the input market or decide not to exercise market power in the retail market, they may be able to reduce consumer expenditure effectively. Our setting indeed features these two conditions.

The political rewards of public firms could be interpreted as showing that, as a whole, public firms increased welfare. However, we highlight the fact that recent research shows that people may over-value policies when they do not internalize the general equilibrium effects that affect them (Dal Bó et al., 2018). Our findings are somewhat consistent with this interpretation, as the majority of consumers in the market are worse off after the entry of public pharmacies due to increased private pharmacy prices.[37] These findings highlight the need to evaluate the market effect of policies instead of drawing conclusions on their desirability based on voting behavior.

Our analysis leaves many questions for future research. Of particular relevance is understanding the choice of quality among public firms. If the quality of public firms was higher, we would expect more consumers to switch to them and the stronger the equilibrium effects towards the private sector. However, changes in the quality of public firms could influence their targeting properties by modifying the population that adopts them (Kleven and Kopczuk, 2011). Furthermore, it is also possible that a higher quality of public firms triggers other strategic responses in the private sector. In the context of retail, these could include changes in the location, prices, or quality of private stores. Our findings thus call for attention to how the interplay between public and private firm attributes may shape equilibrium effects in the market and determine the overall and distributional impacts of public firms.

[37]Recent work by Illanes and Moshary (2020) on the deregulation of retail liquor markets in Washington state also finds evidence consistent with this phenomenon.

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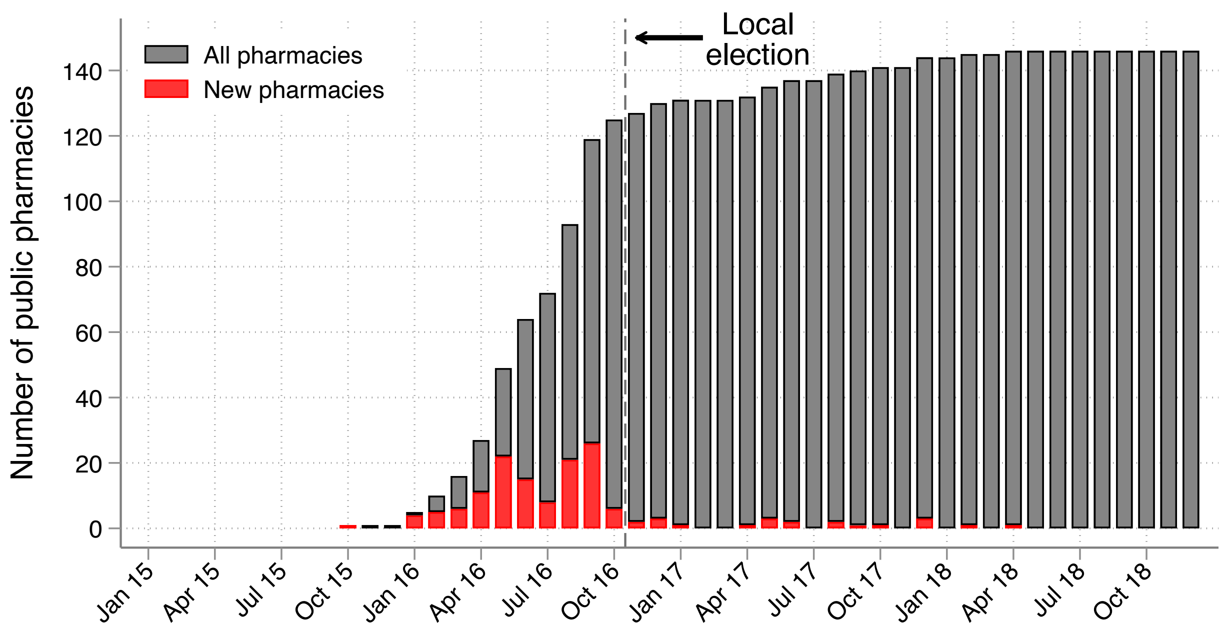
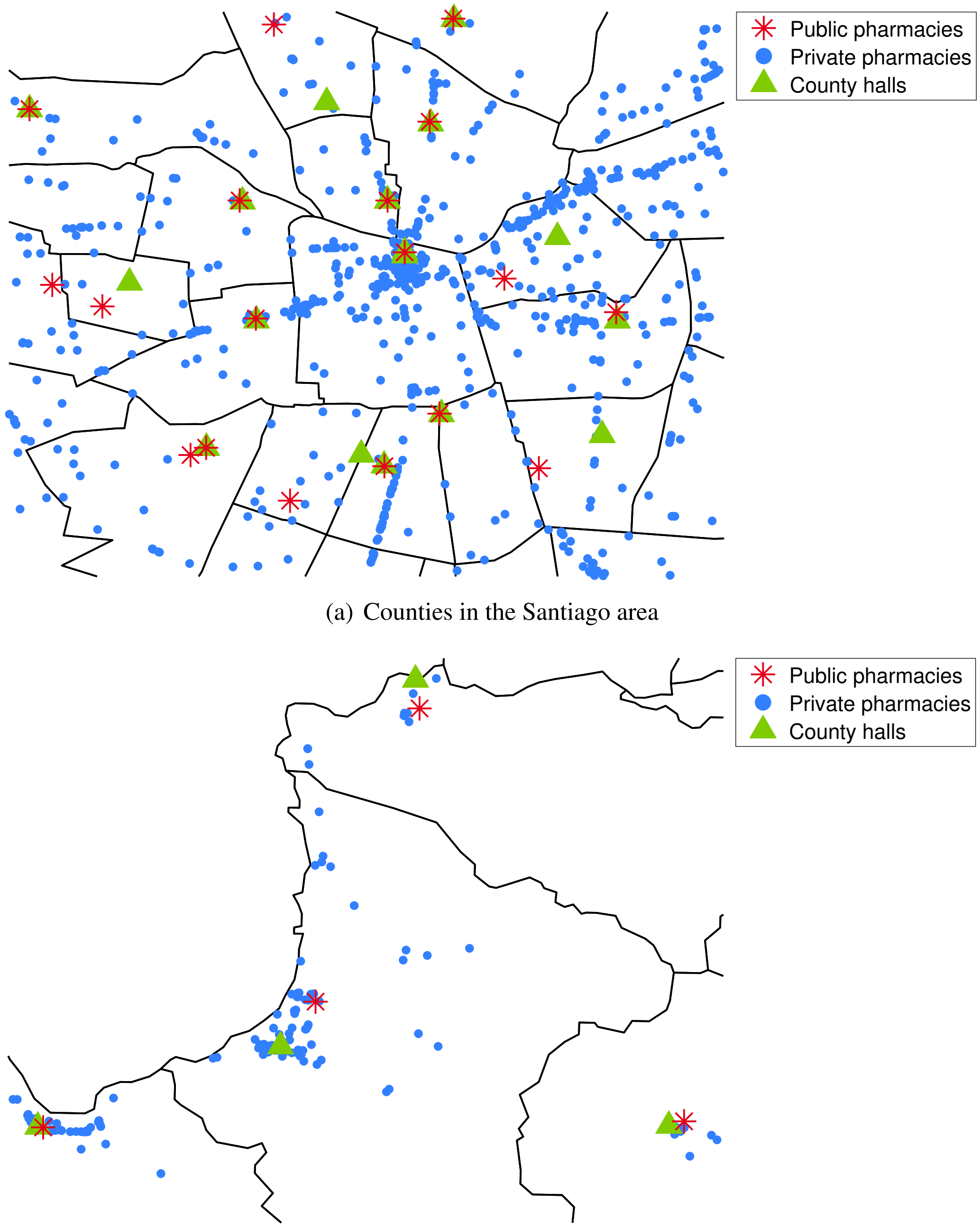
Figure 1: Timing of entry of public pharmacies



Notes: The height of black bars indicate the number of active public pharmacies in a month. The height of red bars indicate the number of new public pharmacies opened in a month.

Figure 2: Locations of public pharmacies

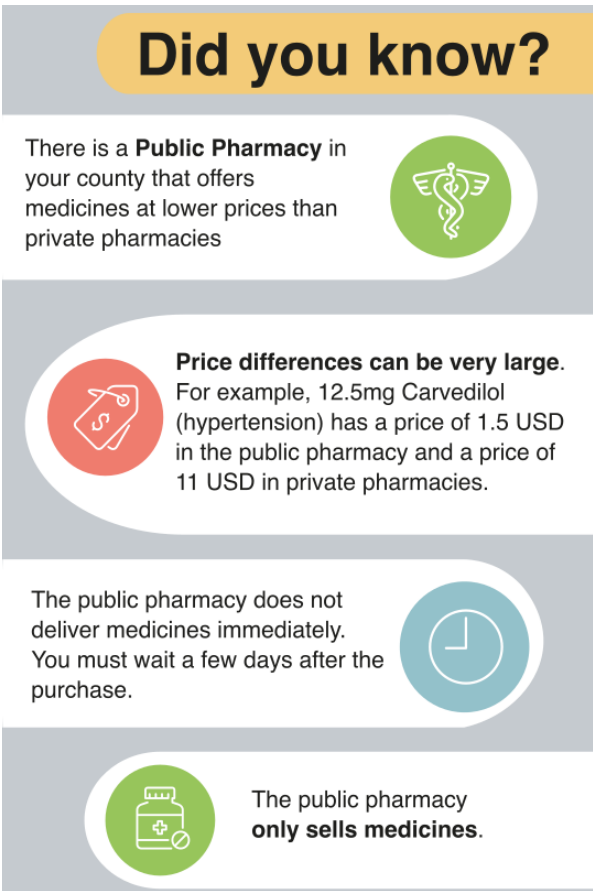


(a) Counties in the Santiago area

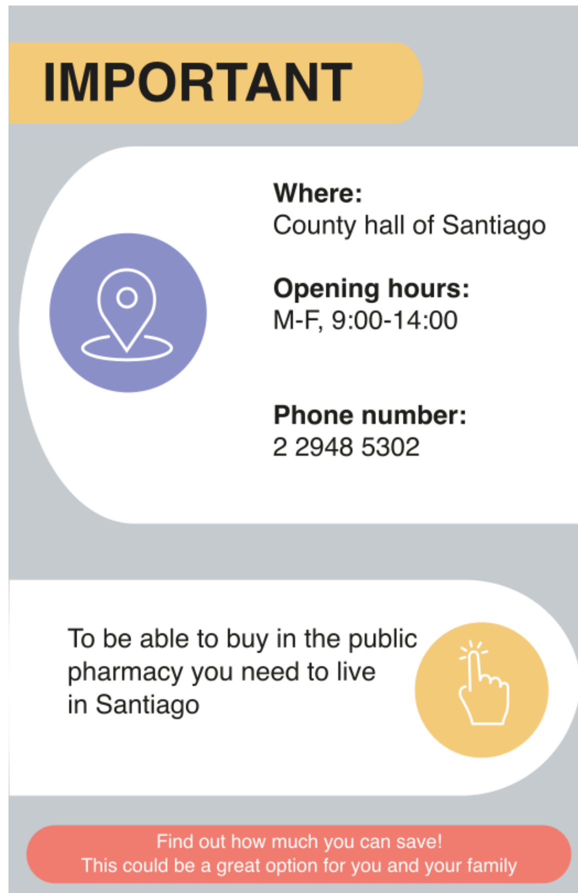
(b) Counties in the Valparaiso area

Notes: Each map displays the geo-coded location of private pharmacies, public pharmacies, and county halls.

Figure 3: Informational treatment



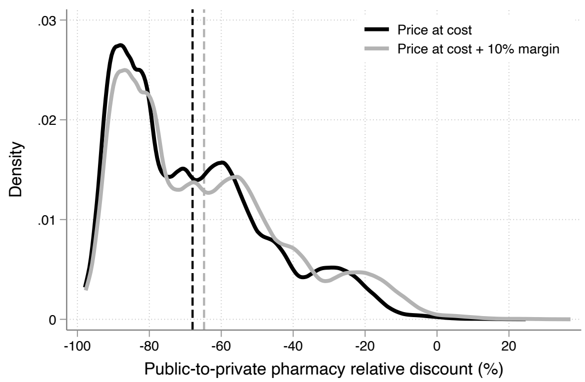
(a) Awareness and convenience



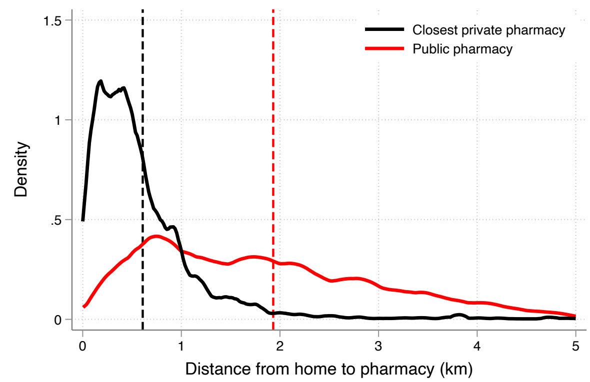
(b) Search details

Notes: This figure displays the informational interventions delivered as part of the field experiment. Panel (a) displays the first part of the treatment, which aimed at increasing awareness about the public pharmacy. It introduces the public pharmacy and mentions that it offers lower prices than private pharmacies and that it may take longer to deliver the products. Panel (b) displays the second part, which aimed at reducing search costs for participants, by including detailed location and contact information for the public pharmacy, hours of attention and eligibility requirements, tailored to the county of each participant.

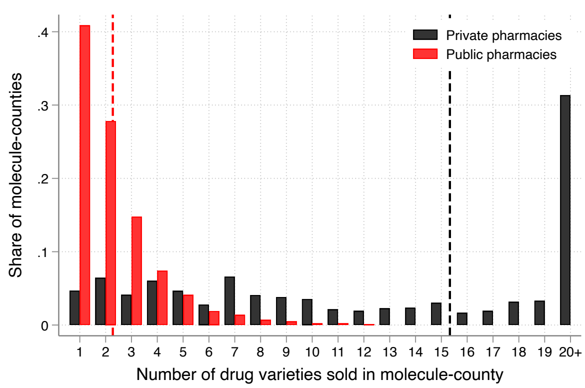
Figure 4: Relative prices between private and public pharmacies



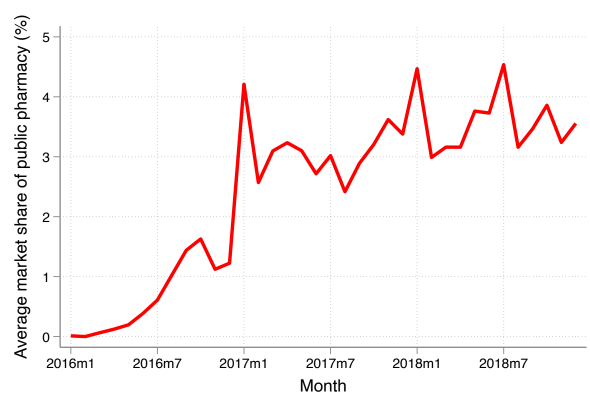
(a) Distribution of price discounts



(b) Distance to pharmacies



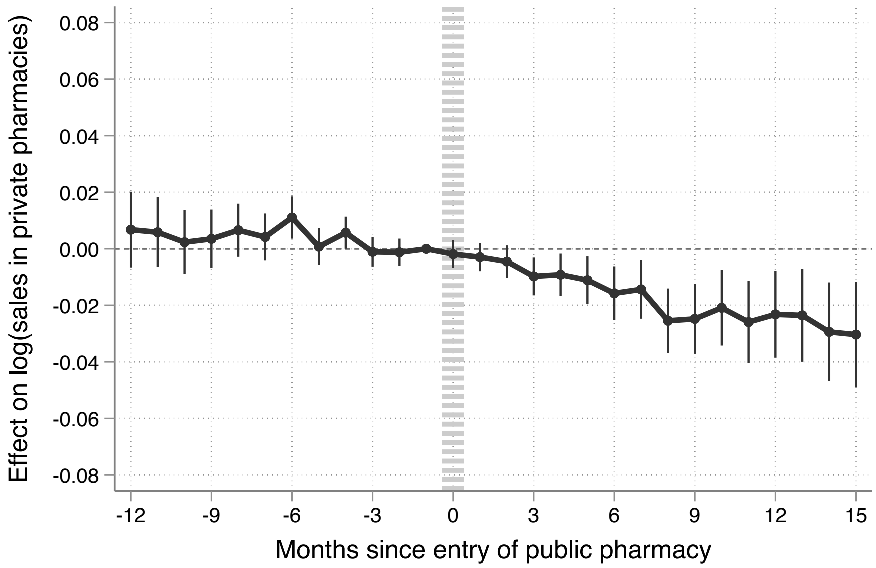
(c) Number of drug varieties



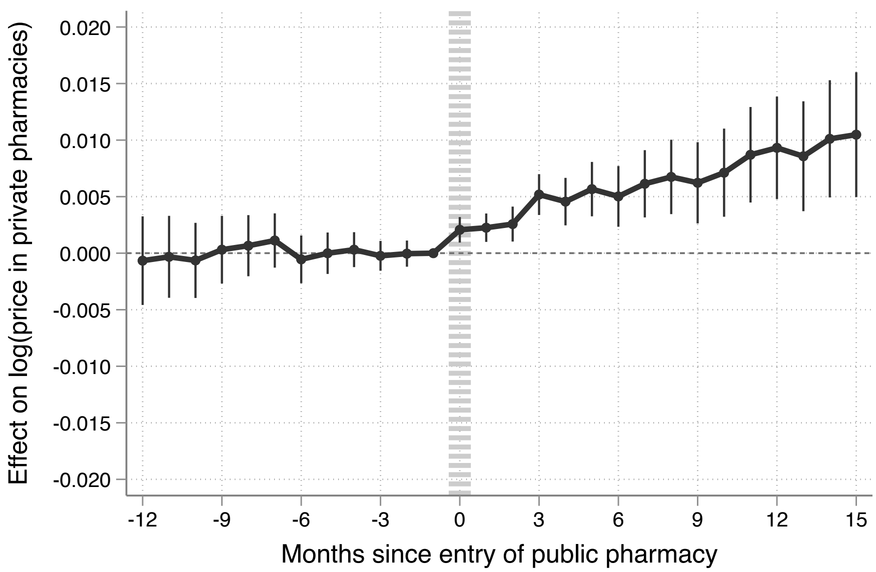
(d) Evolution of market share of public pharmacies

Notes: Panel (a) displays the distribution of proportional discounts of drugs at public pharmacies relative to private pharmacies. The plot is computed using a matched sample of the exact same drug observed in both the CENABAST and IQVIA datasets for a given county and month during 2017–2018. Because the CENABAST data only provides the cost to public pharmacies, we compute price discounts for public pharmacies pricing at cost (black) and at a margin of 10 percent over cost (gray). The dashed vertical lines indicate the mean price discount for each scenario. Panel (b) shows the density of distance to the closest private pharmacy (black) and to the public pharmacy in counties with a public pharmacy. The dashed vertical lines indicate the respective means of both distributions. Panel (c) describes the number of drug presentations of a given molecule sold in a county over 2017–2018 for private (black) and public (red) pharmacies, whenever both private and public pharmacies sell at least one drug of the molecule. Panel (d) displays the average market share across molecules and counties in each month during 2016–2018.

Figure 5: Impact of public pharmacies on sales and prices in private pharmacies



(a) Sales



(b) Prices

Notes: This figure presents the coefficients of the stacked event study specification in equation (2). Locations with multiple events are stacked multiple times in the data. The timing of entry is defined as the *largest* county to introduce a public pharmacy in the set of counties in location *l*. Panel (a) displays results for drug sales, whereas Panel (b) displays results for drug prices. Dots indicate estimated coefficients, and vertical lines indicate the corresponding 95 percent condence intervals.

Table 1: Balance in covariates between treatment and control group

Variable	(1) Control	(2) Treatment	(3) p-value $H_0 : (1) = (2)$
Age	45.25	46.32	0.39
	(16.81)	(17.50)	
Education higher than HS (=1)	0.54	0.51	0.44
	(0.50)	(0.50)	
Female (=1)	0.60	0.63	0.47
	(0.49)	(0.48)	
Days with internet (0-7)	5.47	5.23	0.23
	(2.71)	(2.84)	
Works (=1)	0.62	0.64	0.53
	(0.49)	(0.48)	
Support for incumbent (=1)	0.50	0.51	0.86
	(0.50)	(0.50)	
Voted in previous election (=1)	0.73	0.74	0.68
	(0.44)	(0.44)	
Knows public pharmacy (=1)	0.61	0.67	0.09
	(0.49)	(0.47)	
Observations	319	507	

Notes: Columns 1 and 2 display the mean and standard deviation of different covariates at baseline for each experimental group. Column 3 displays the p-value from a test of equality of means across the groups.

Table 2: An empirical examination of the entry decision of public pharmacies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Counties with public pharmacy						
	All	Opened *before* 2016 election	Opened *after* 2016 election	Counties without public pharmacy	Differences (1)–(4)	(2)–(3)	Timing of entry
Pharmacies and hospitals							
Private pharmacies per 100,000 inhab.	13.57	13.83	12.01	7.71	5.86***	1.85	-0.003
Log sales in private pharmacies	15.37	15.41	15.09	15.15	0.21**	0.32*	-0.465
Price index in private pharmacies	931	928	949	872	59**	-20	0.001
Hospitalizations per 100,000 inhab.	9,430	9,444	9,344	8,127	1,302***	112	0.00
Deaths per 100,000 inhab.	208	210	200	177	31***	10	-0.02
Socioeconomic characteristics							
Log household income	12.97	12.98	12.93	12.61	0.37***	0.06	-0.467
Age of inhabitants	44.50	44.44	44.84	45.68	-1.18***	-0.40	0.115
Average unemployment rate	0.10	0.10	0.10	0.09	0.02***	0.01	7.091
Share with public health insurance	0.83	0.83	0.85	0.89	-0.06***	-0.02	1.400
Self reported health (1-7)	5.54	5.54	5.51	5.49	0.05*	0.03	1.900
Number of doctor visits	0.32	0.31	0.32	0.30	0.02	-0.01	1.359
Population (in 10,000)	9.60	10.26	5.63	1.88	7.72***	4.70**	-0.425**
Political characteristics							
Number of competitors	3.56	3.61	3.29	3.20	0.36***	0.34	0.121
Winning margin	0.19	0.19	0.22	0.17	0.02	-0.03	-3.768
Vote share winner	0.54	0.53	0.56	0.53	0.01	-0.02	5.951
Incumbent coalition wins	0.62	0.63	0.60	0.57	0.05	-0.03	0.439
Incumbent coalition: independent	0.31	0.31	0.33	0.35	-0.03	0.02	-0.045
Incumbent coalition: left-wing	0.46	0.48	0.33	0.37	0.10*	0.15	-1.161**
Incumbent coalition: right-wing	0.22	0.21	0.33	0.29	-0.06	-0.13	–
Number of counties	147	126	21	197	–	–	147

Notes: Counties with and without public pharmacy until July 2018. "Pharmacies and hospitals" are own construction using data from the Public Health Institute and IQVIA in 2014. "Socioeconomic characteristics" are own construction using data from the 2015 National Socioeconomic Characterization. "Political characteristics" are own construction using data from Chile's Electoral Service. Column 7 reports coefficients from a cross-sectional ordered logit using the order in which public pharmacies opened as dependent variable – the first pharmacy has a value of one – and all market and political characteristics as explanatory variables. Differences in mean across columns 2 and 3 use a permutation test to correct for the small sample. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Experimental results for economic outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A - Knowledge about public pharmacies								
	1(Knows about pharmacy)			log(Perceived price)			log(Perceived waiting time)		
Treatment	0.092***	0.056***		-0.117**	-0.094**		0.173	0.188*	
	(0.027)	(0.019)		(0.046)	(0.045)		(0.107)	(0.103)	
Treatment × chronic (β_C)			0.027			-0.114*			0.134
			(0.025)			(0.061)			(0.140)
Treatment × non-chronic (β_{NC})			0.098***			-0.063			0.264*
			(0.031)			(0.065)			(0.151)
Dependent variable at baseline		0.496***	0.495***		0.382***	0.382***		0.397***	0.399***
		(0.038)	(0.038)		(0.049)	(0.049)		(0.068)	(0.068)
Mean for control group		0.820			9.070			1.387	
Lee bounds		[0.087**, 0.093***]			[-0.236***, -0.020]			[0.049 , 0.189]	
p-value for H_0: $\beta_C = \beta_{NC}$	-	-	0.076	-	-	0.570	-	-	0.531
Observations	702	702	702	498	491	491	445	425	425
R-squared	0.018	0.490	0.493	0.012	0.197	0.197	0.006	0.181	0.182
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
	Panel B - Usage of public pharmacies								
	1(Enrolled)			1(Purchased)			Probability of usage		
Treatment	0.018	0.020		0.019	0.023		0.060*	0.054	
	(0.024)	(0.024)		(0.017)	(0.018)		(0.035)	(0.036)	
Treatment × chronic (β_C)			0.032			0.043*			0.085*
			(0.033)			(0.024)			(0.046)
Treatment × non-chronic (β_{NC})			0.002			-0.008			-0.008
			(0.034)			(0.026)			(0.057)
Knows pharmacy at baseline		0.050**	0.050**		0.015	0.015		-0.042	-0.045
		(0.021)	(0.021)		(0.017)	(0.017)		(0.043)	(0.043)
Lee bounds		[0.007, 0.087***]			[0.015, 0.047***]			[0.060 , 0.083]	
p-value for H_0: $\beta_C = \beta_{NC}$	-	-	0.524	-	-	0.155	-	-	0.213
Mean for control group	0.069	0.069	0.069	0.028	0.028	0.028	0.540	0.540	0.540
Observations	514	514	514	514	514	514	387	387	387
R-squared	0.001	0.021	0.100	0.002	0.008	0.067	0.008	0.008	0.057
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Notes: This table displays results for three versions of equation (1), where the first one includes only a treatment dummy as regressor, the second one includes the baseline level of the dependent variable, additional control variables and county fixed effects, and the third one interacts the treatment dummy with an indicator for whether a member of the consumer household has a chronic condition. The set of control variables includes age, and indicators for chronic condition, having completed high school education, female and public insurance. Outcomes in Panel B either do not have baseline counterparts (which is the case by design of indicators for enrollment and purchase) or were not collected at baseline (which is the case for the probability of usage), so we instead control for knowledge of the public pharmacy at baseline. Reported Lee bounds are computed using only the treatment dummy as a covariate. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effect on drug sales and prices in the private market

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+sales)			log(price)		
PP index	-0.038***	-0.041***		0.008***	0.011***	
	(0.011)	(0.006)		(0.003)	(0.001)	
PP index × chronic (β_C)			-0.055***			0.008***
			(0.007)			(0.002)
PP index × non-chronic (β_{NC})			-0.020**			0.015***
			(0.009)			(0.003)
p-value for H_0: $\beta_C = \beta_{NC}$	-	-	0.003	-	-	0.024
Observations	681,120	681,120	681,120	649,885	649,885	649,885
R-squared	0.014	0.543	0.543	0.520	0.848	0.848
Molecule FE	Yes	No	No	Yes	No	No
Month FE	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No
Molecule-by-Month FE	No	Yes	Yes	No	Yes	Yes
Molecule-by-Location FE	No	Yes	Yes	No	Yes	Yes

Notes: This table displays estimates of equation (3). The treatment variable is the share of the population living in location l that have access to a public pharmacy at time t. In columns 3 and 6, exposure to public pharmacies is interacted with an indicator for whether a molecule is targeted towards a chronic condition or not. Standard errors clustered at the molecule-by-location level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Municipal finance

	(1)	(2)	(3)	(4)	(5)	(6)
	Health services		Non-health services		All services	
	Spending	Revenue	Spending	Revenue	Spending	Revenue
Public pharmacy	0.051***	0.038**	-0.046	-0.045	0.013	0.008
	(0.018)	(0.019)	(0.032)	(0.033)	(0.015)	(0.015)
p-value for $H_0 : \delta_{\text{spending}} = \delta_{\text{revenue}}$	0.066		0.976		0.579	
Mean of dep. var. in 2014	164.66	163.13	434.31	465.16	632.36	664.75
Observations	2,223	2,223	2,226	2,226	2,226	2,226
R-squared	0.964	0.957	0.942	0.933	0.973	0.970
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Annual data for all counties in the period 2013–2019. Spending and revenue are measured as the log of each variable measured in U.S dollars per capita. Standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effect on avoidable hospitalizations associated to chronic diseases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Avoidable hospitalizations per 100,000 inhabitants							
	Number of hospitalizations		Days of hospitalizations		Number of surgeries		Number of deaths	
Public pharmacy	0.082	-0.196	1.074	1.716	0.089	0.076	0.070	0.077
	(0.584)	(0.626)	(5.469)	(6.012)	(0.112)	(0.131)	(0.049)	(0.053)
Health insurance	All	Public	All	Public	All	Public	All	Public
Mean of dep. var. in 2014	17.95	19.20	158.8	173.3	1.735	1.917	0.748	0.842
Observations	24,768	24,768	24,768	24,768	24,768	24,768	24,768	24,768
R-squared	0.472	0.745	0.264	0.732	0.144	0.687	0.062	0.736
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays results from estimating equation (4). For each outcome, the first column uses the count of the outcome per 100,000 inhabitants in a county regardless of individual health insurance, and the second column restricts that count to individuals with publicly provided insurance (FONASA). We report the mean of the dependent variable for 2014 among counties that ever introduce a public pharmacy, the year before most public pharmacies entered the market. Standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Experimental results for political outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Voted incumbent mayor			Voted incumbent party			Voted in the election		
Treatment	0.057	0.075*		0.064	0.056		0.066	0.052	
	(0.045)	(0.039)		(0.040)	(0.035)		(0.046)	(0.044)	
Treatment × chronic (β_C)			0.080			0.081*			0.040
			(0.051)			(0.044)			(0.055)
Treatment × non-chronic (β_{NC})			0.067			0.020			0.068
			(0.065)			(0.058)			(0.073)
Dependent variable at baseline		0.366***	0.367***		0.348***	0.350***		0.418***	0.416***
		(0.051)	(0.051)		(0.048)	(0.048)		(0.052)	(0.052)
Lee bounds	[0.033, 0.182***]			[0.048, 0.170***]			[0.014, 0.159**]		
p-value for H_0: $\beta_C = \beta_{NC}$	-	-	0.883	-	-	0.408	-	-	0.763
Mean for control group	0.281	0.277	0.277	0.263	0.255	0.255	0.541	0.524	0.524
Observations	398	368	368	475	435	435	475	435	435
R-squared	0.004	0.515	0.515	0.005	0.488	0.488	0.004	0.641	0.641
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Notes: This table displays results for three versions of equation (1), where the first one includes only a treatment dummy as regressor, the second one includes the baseline level of the dependent variable, additional control variables and county fixed effects, and the third one interacts the treatment dummy with an indicator for whether a member of the consumer household has a chronic condition. The set of control variables includes age, and indicators for chronic condition, having completed high school education, female and public insurance. Reported Lee bounds are computed using only the treatment dummy as a covariate. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Evaluation of mayors who opened pharmacies *before* the 2016 local election

	(1)	(2)	(3)
	Vote share incumbent coalition	Vote share incumbent mayor	Turnout
Log distance from voters' home to pharmacy	-0.081***	-0.106***	0.037
× Opened *before* the election	(0.025)	(0.021)	(0.025)
Log age of voters in booth	0.053*	0.054*	0.021
× Opened *before* the election	(0.028)	(0.030)	(0.034)
Mean of the dependent variable (%)	0.50	0.50	0.34
Number of booths	3,825	3,376	3,825
Number of voters	1,272,474	1,131,494	1,272,474
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes

Notes: This table uses a cross-sectional sample of 3,855 booths in 141 counties with an active public pharmacy until February 2018. The estimation uses 141 counties in columns (1) and (3), and 120 counties in column (2), i.e. in 21 counties the incumbent mayor did not run for reelection. We interpret distance from voters' home to the public pharmacy as the geographic exposure of voters, and the age of voters as a proxy for the likelihood of having a chronic disease and hence use the public pharmacy. Controls include the share of women in the booth, the average age of voters in the booth, the (log of) the distance between voters' home and city hall, voter's home and their booth, and voters' booth and the pharmacy, and the same variables interacted by an indicator that takes the value of one for counties with pharmacies that opened before the 2016 elections. Standard errors are clustered at the county level.

ONLINE APPENDIX

The Economics of the Public Option: Evidence from Local Pharmaceutical Markets

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A Additional results on economic outcomes

A.1 Alternative specifications of the event study

In our main specification we use a stacked event study regression. In this section, we provide results using standard event study regressions with unique entry events at the location level. The estimation equation in this case is a simple version of equation (2) given by:

$$y_{mlt} = \sum_{k=-12}^{15} \beta_k D_{lt}^k + \lambda_{mt} + \theta_{ml} + \varepsilon_{mlt}$$

Since there is no obvious way to define unique entry events in our setting, we provide results using two alternative definitions of the event. In the first case, we define the event as the date that a public pharmacy was *first* introduced by a county in a location l. The second definition uses the date that the *largest* county in the location introduced a public pharmacy, among counties for which there is an entry event. Figures A.6 and A.7 display the results for each definition of the event. In both cases, we find no differential pre-trends in sales and prices, and the results are quantitatively consistent with the findings using the stacked event study regression.

A.2 Decomposition of price effects

To further study the effect of public pharmacies on prices, we adapt the decomposition developed by Atal et al. (2019) to our setting. This procedure decomposes the evolution of average paid prices on terms associated with price changes—the result we report in the main text—, share changes, the correlation between those, product entry and product exit.

Let the log price per gram of a drug i in location l and month t be P_{ilt}. Define the set of drugs in location l, molecule m and month t that were also in the market in the baseline period as $\mathcal{S}_{mlt} \equiv \mathcal{I}_{mlt} \cap \mathcal{I}_{ml0}$; the set of drugs that entered market m after the baseline period and remain in the market in period t as $\mathcal{E}_{mlt} \equiv \mathcal{I}_{mlt} \setminus \mathcal{I}_{ml0}$; and the set of drugs that exited between the baseline period and t as $\mathcal{X}_{mlt} \equiv \mathcal{I}_{ml0} \setminus \mathcal{I}_{mlt}$. Then, we decompose the change in the share-weighted average of log prices between a baseline month $t = 0$ and month t as:

$$\begin{aligned}
\underbrace{\sum_{i \in \mathcal{I}_{mlt}} w_{ilt} P_{ilt} - \sum_{i \in \mathcal{I}_{ml0}} w_{il0} P_{il0}}_{\equiv \hat{P}_{mlt} - \hat{P}_{ml0}} \quad = \quad & \underbrace{\sum_{i \in \mathcal{S}_{mlt}} w_{il0} (P_{ilt} - P_{il0})}_{\equiv \Delta P_{mlt,C}} + \underbrace{\sum_{i \in \mathcal{S}_{mlt}} (P_{ilt} - P_{ml0})(w_{ilt} - w_{il0})}_{\equiv \Delta P_{mlt,RW}} \\
& + \underbrace{\sum_{i \in \mathcal{S}_{mlt}} (w_{ilt} - w_{il0})(P_{ilt} - P_{il0})}_{\equiv \Delta P_{mlt,CS}} + \underbrace{\sum_{i \in \mathcal{E}_{mlt}} w_{ilt} (P_{ilt} - P_{ml0})}_{\equiv \Delta P_{mlt,E}} \\
& - \underbrace{\sum_{i \in \mathcal{X}_{mlt}} w_{il0} (P_{il0} - P_{ml0})}_{\equiv \Delta P_{mlt,X}}
\end{aligned}$$

where $\Delta P_{mlt,C}$ measures the change in the share-weighted average price due to price changes among incumbent drugs, holding weights fixed; $\Delta P_{mlt,RW}$ measures the change in the share-weighted average due to changes in relative market shares, holding prices fixed; $\Delta P_{mlt,CS}$ measures the change in share-weighted prices due to the correlation between price changes and changes in market shares; $\Delta P_{mlt,E}$ captures price changes due to the entry of drugs in the market and $\Delta P_{mlt,X}$ measures the change in the share-weighted average due to the exit of drugs.

Therefore, share-weighted log prices can be decomposed as:

$$\hat{P}_{mlt} = \hat{P}_{ml0} + \Delta P_{mlt,C} + \Delta P_{mlt,RW} + \Delta P_{mlt,CS} + \Delta P_{mlt,E} + \Delta P_{mlt,X} \tag{6}$$

To estimate the effect of public pharmacies on each component of the evolution of prices, we estimate equation (3) using $\hat{P}_{mt,C} \equiv \hat{P}_{m0} + \Delta P_{mt,C}$, $\hat{P}_{mt,RW} \equiv \hat{P}_{m0} + \Delta P_{mt,RW}$, $\hat{P}_{mt,CS} \equiv \hat{P}_{m0} + \Delta P_{mt,CS}$, $\hat{P}_{mt,E} \equiv \hat{P}_{m0} + \Delta P_{mt,E}$ and $\hat{P}_{mt,X} \equiv \Delta \hat{P}_{m0} + P_{mt,X}$ as dependent variables.

The effect of public pharmacies on average paid prices at private pharmacies is somewhat larger that the on price changes by the latter, discussed in section 5.3. Figure A.8 shows estimates from our event study specification in equation (2) for average paid prices. As for the case of price changes, these results show a steady increase in prices after the entry of public pharmacies, with no evidence of differential trends leading to that event.

Most of the increase in overall average paid prices is driven by within-drug price changes. Table A.4 shows that average paid prices increased by 1.7 percent as a result, of which price changes accounted for 1.1 percent. The remainder of the effect in average paid prices is driven mostly by entry of products with higher prices to the market following the entry of public pharmacies.

B Persuasion rate of public pharmacies

This section provides details about public pharmacies in terms of their persuasion rate, a common tool used in political economy to estimate the impact of media on voters (Enikolopov et al., 2011). Let v_0 be the share of voters supporting the incumbent mayor in a counterfactual scenario without public pharmacies. Let p be defined as the "persuasion rate" of public pharmacies and e the percentage of potential voters (1) geographically exposed to the pharmacy, or (2) the informational treatment. Then the total number of people who supported the incumbent mayor who opened the pharmacy in the 2016 local election can de written as:

$$v = v_0 + (1 - v_0) \cdot e \cdot p \tag{7}$$

where the term $(1-v_0)\cdot e$ represents the group of people who planned on voting for a challenger and were directly (with chronic disease) or indirectly (without chronic disease) exposed to the public pharmacy. We want to calculate the persuasion rate p, the percentage of people exposed to the pharmacy (or information about it) that were persuaded to vote for the incumbent mayor because of the public option. To achieve this goal, let us express the percentage of voters who would have voted for the challenger in the absence of the pharmacy (v_0) as a function of turnout (t_0) and vote shares (s_0). Then we can take equation (7) and differentiate with respect to e to obtain:

$$p = \frac{1}{1 - s_0 t_0} \times \left(s\frac{\partial t}{\partial e} + t\frac{\partial s}{\partial e} \right) \tag{8}$$

with s and t representing the observed vote share for the incumbent mayor and turnout in the election respectively. Thus the persuasion rate is a simply function of our estimates. Please note that in our context we have that $\frac{\partial t}{\partial e} = 0$, hence we conjecture that $t = t_0 = 0.35$, the actual turnout rate in the 2016 local election. We also estimate that $\frac{\partial s}{\partial e}$ equals 7–11 percent in the informational experiment. In addition, we use $s_0 = 0.35$ but results are robust to small deviations. Then, we estimate a persuasion rate of $p = 0.04$ in the general population.

Figure A.1: Examples of private and public pharmacy

(a) Outside of private pharmacy

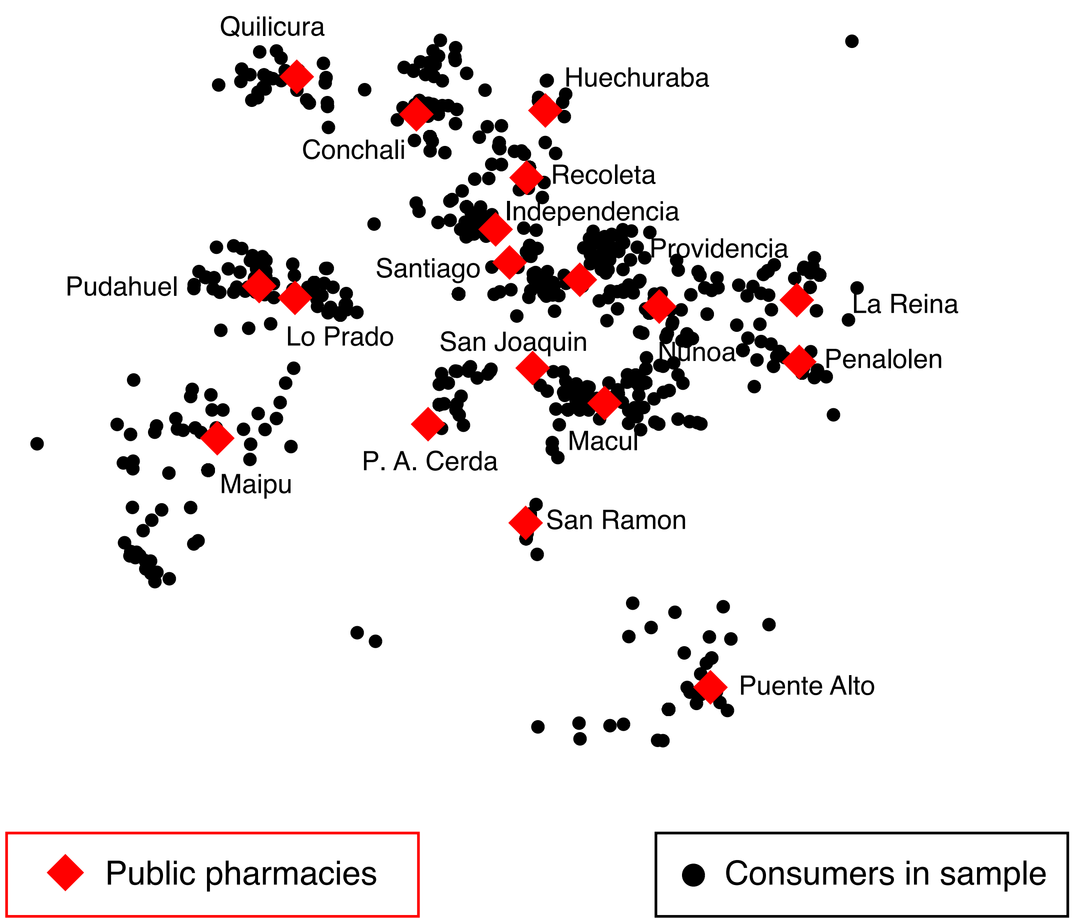
(b) Inside of private pharmacy

(c) Outside of public pharmacy

(d) Inside of public pharmacy

Notes: This figure displays photos of private and public pharmacies from the outside and inside. The private pharmacy in panels (a) and (b) is a somewhat generic building and it is part of one of the leading chains. The public pharmacy in panels (c) and (d) is located in the capital city and it is part of our experimental sample.

Figure A.2: Location of pharmacies and consumers in experimental sample



Notes: This figure displays the location of public pharmacies and consumers included included in the experimental sample.

Figure A.3: Timeline of experiment events

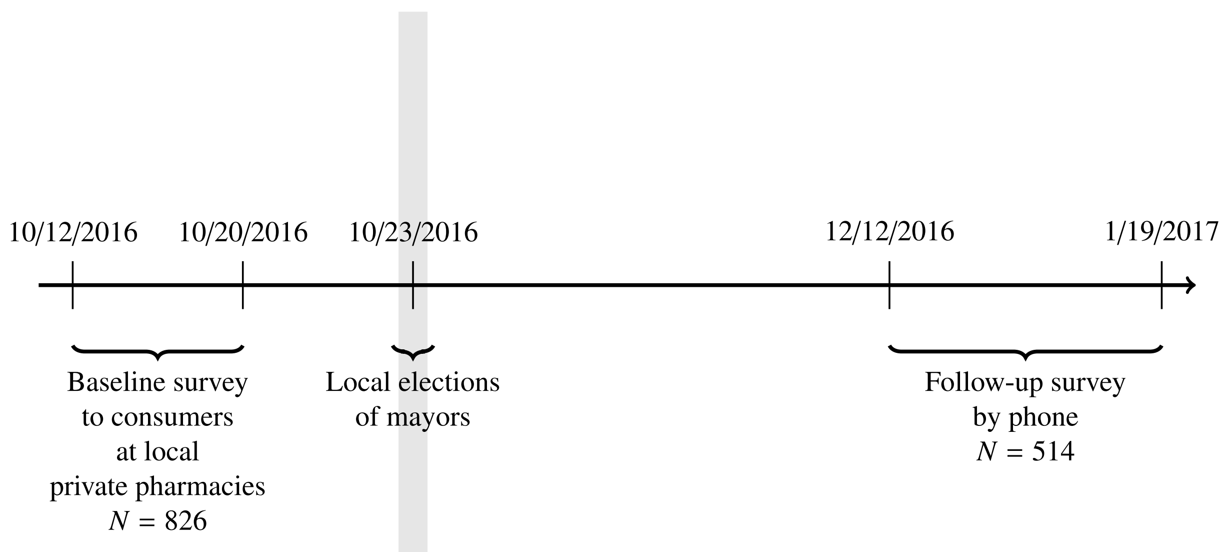
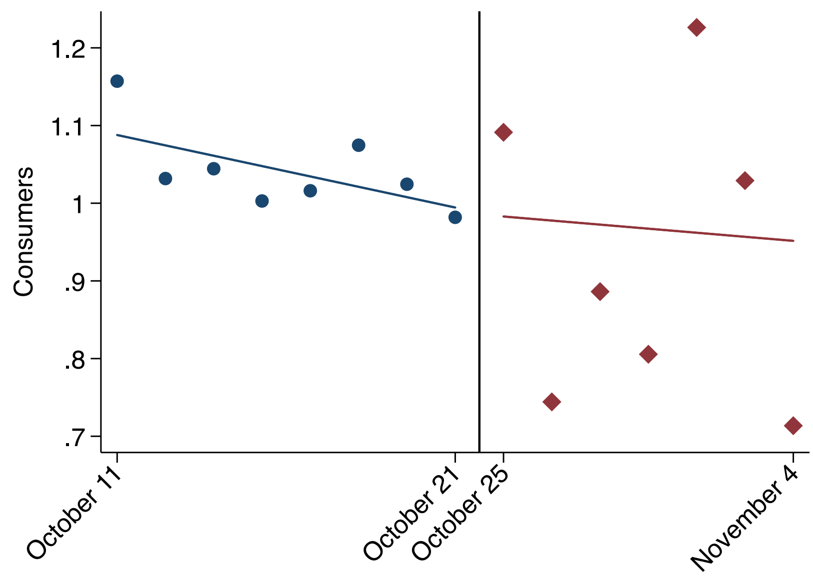
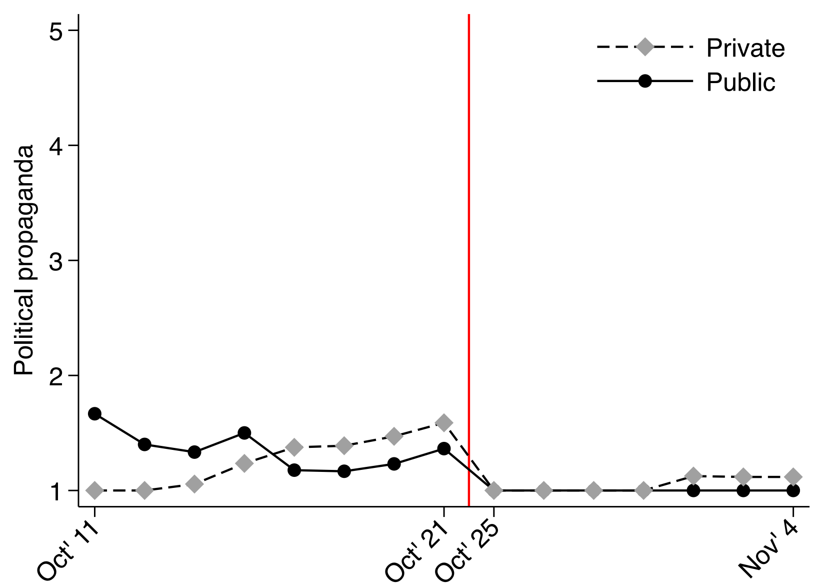


Figure A.4: Monitoring pharmacies around local elections



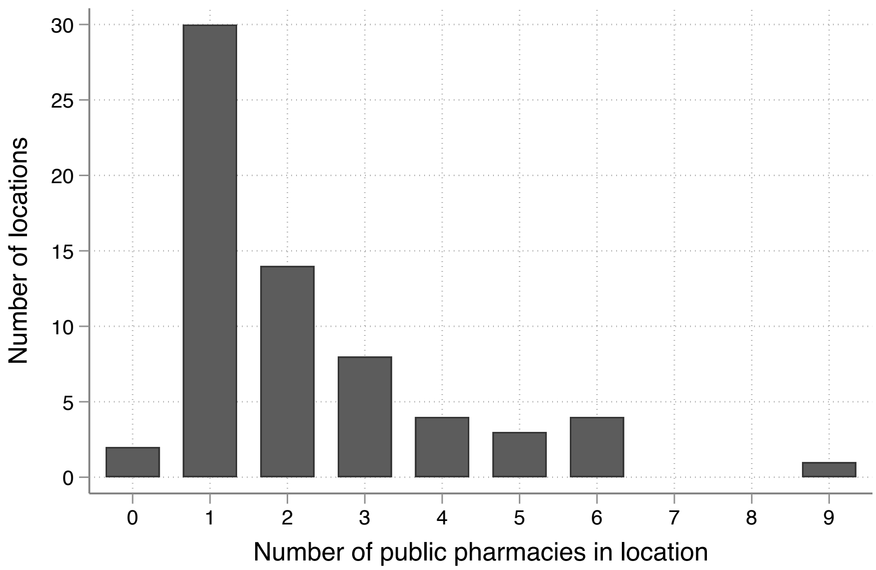
(a) Consumers per hour in public pharmacies



(b) Propaganda

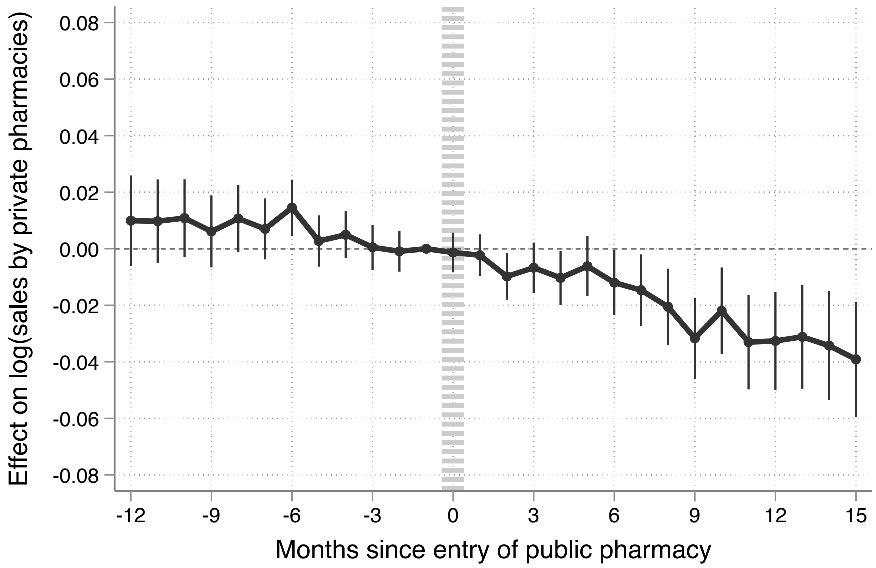
Notes: Panel (a) plots the number of consumers per hour in public and private pharmacies. We normalized to 1 the day before the election to facilitate the comparison. We constructed these data counting the number of people who entered public pharmacies in our experimental sample during 1-hour at the same time two weeks before and after the election. Panel (b) plots the political propaganda as visualized by enumerators. The variable in the *y*-axis is coded as (1) no propaganda, (2) little propaganda, (3) some propaganda, (4) plenty of propaganda, and (5) a lot of propaganda.

Figure A.5: Impact of public pharmacies: Number of events per location

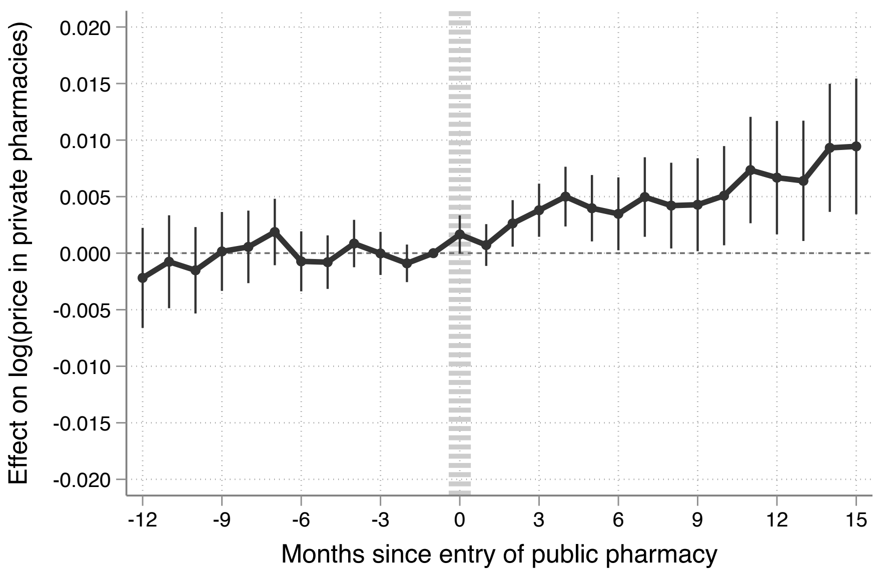


Notes: This figure shows the number of events within a location. An event is defined as the introduction of a public pharmacy in a county,

Figure A.6: Impact of public pharmacies: Entry is first county



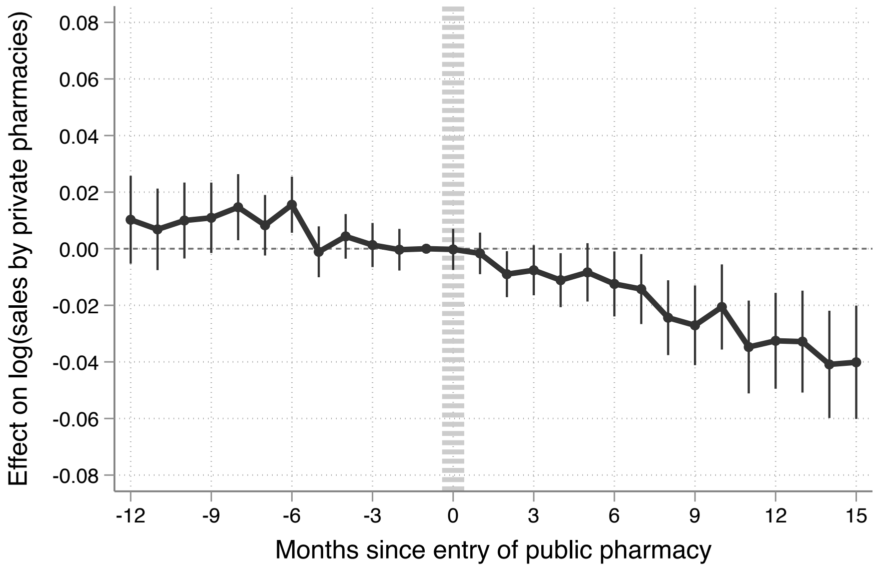
(a) Sales



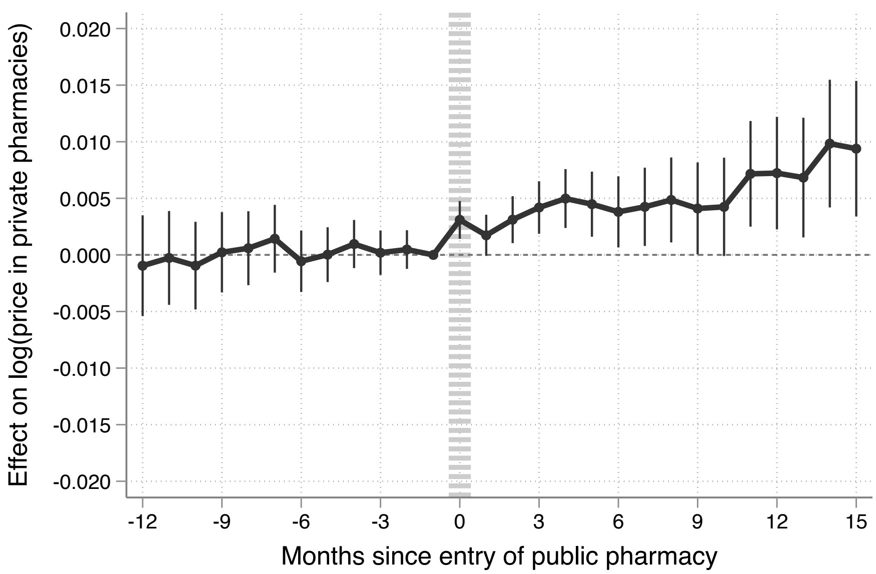
(b) Prices

Notes: This figure presents the coefficients of the event study specification in equation (2), but includes molecule-location fixed effects instead of molecule-location-event fixed effects. Panel (a) displays results for drug sales, whereas Panel (b) displays results for drug prices. Dots indicate estimated coefficients, and vertical lines indicate the corresponding 95 percent condence intervals.

Figure A.7: Impact of public pharmacies: Entry is largest county



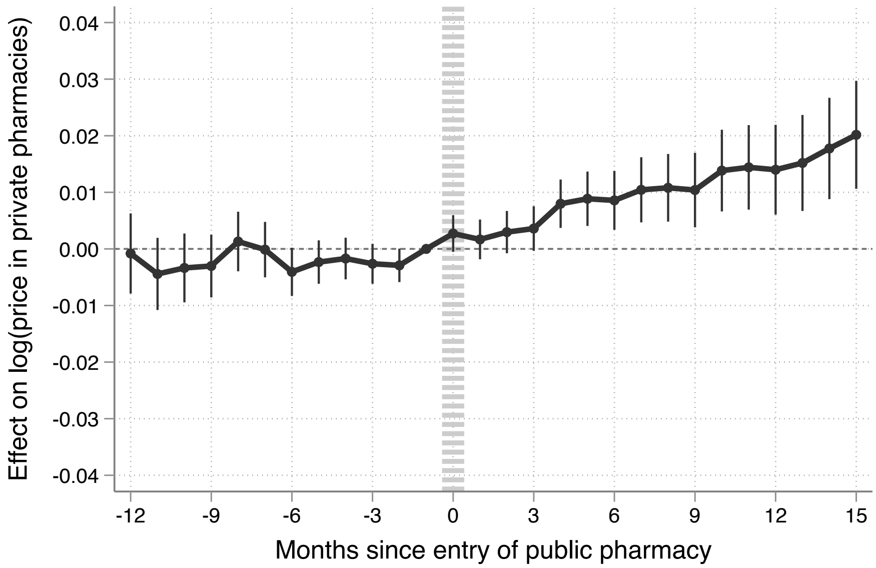
(a) Sales



(b) Prices

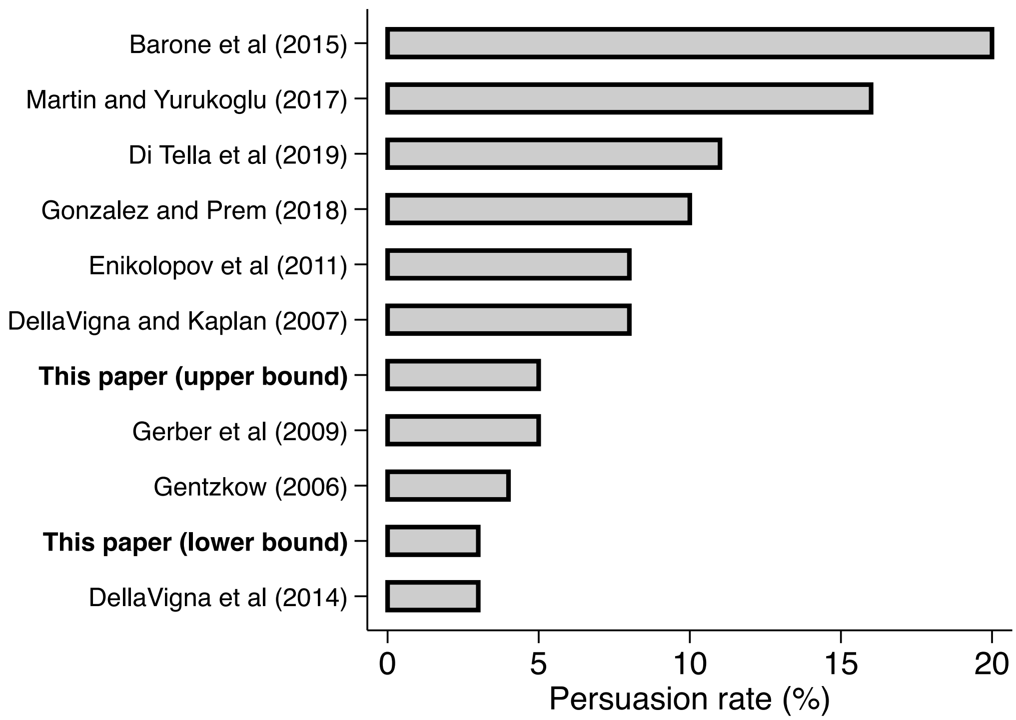
Notes: This figure presents the coefficients of the event study specification in equation (2), but includes molecule-location fixed effects instead of molecule-location-event fixed effects. The timing of entry is defined as the *largest* county to introduce a public pharmacy in the set of counties in location *l*. Panel (a) displays results for drug sales, whereas Panel (b) displays results for drug prices. Dots indicate estimated coefficients, and vertical lines indicate the corresponding 95 percent condence intervals.

Figure A.8: Impact of public pharmacies: Average paid prices



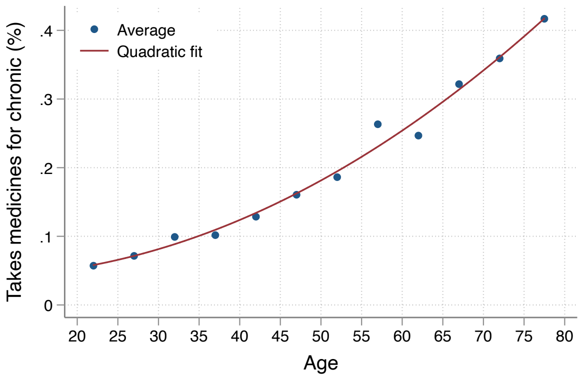
Notes: This figure presents the coefficients of the event study specification in equation (2). The dependent variable measures average paid prices as defined in Appendix A.2. Dots indicate estimated coefficients, and vertical lines indicate the corresponding 95 percent condence intervals.

Figure A.9: Persuasion rates

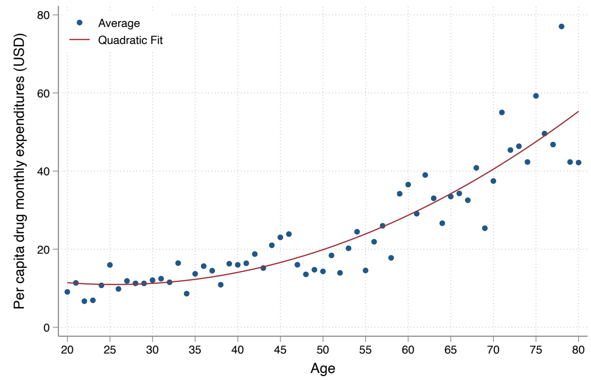


Notes: Own construction based on persuasion rates reported in DellaVigna and Gentzkow (2010).

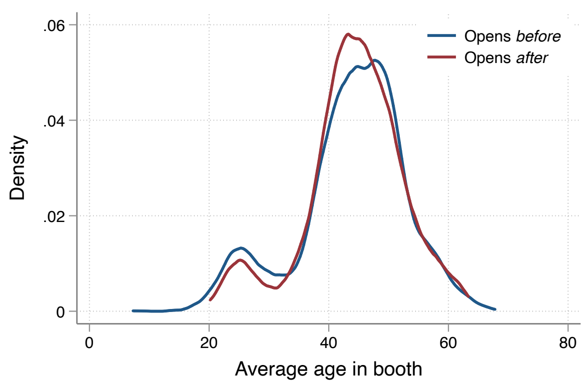
Figure A.10: Age as a proxy for the likelihood of using the public pharmacy



(a) Age and likelihood of chronic disease



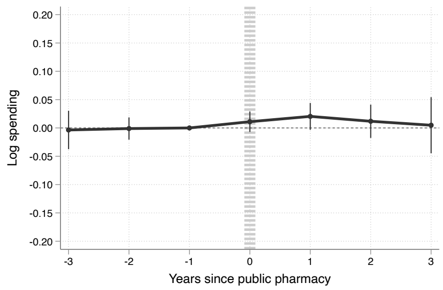
(b) Age and drug expenditures



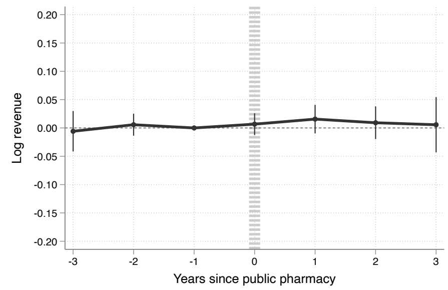
(c) Age distribution and timing of public pharmacy entry

Notes: Panel (a) is based on data from the 2016–2017 National Health Survey. Panel (b) shows average per capita health expenditures as a function of average household age using the 2016 National Household Spending Survey. Panel (c) is based on administrative data from the Electoral Service.

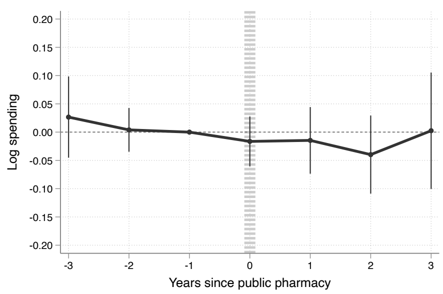
Figure A.11: Event study estimates for effects on municipal finance



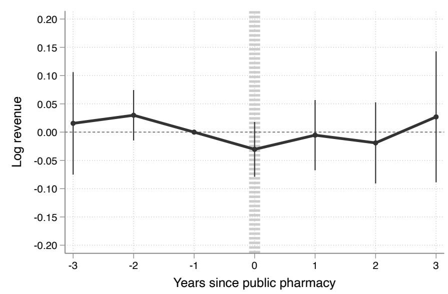
(a) Total spending



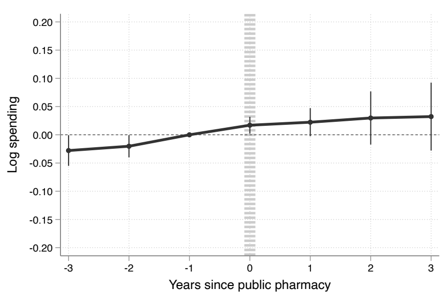
(b) Total revenue



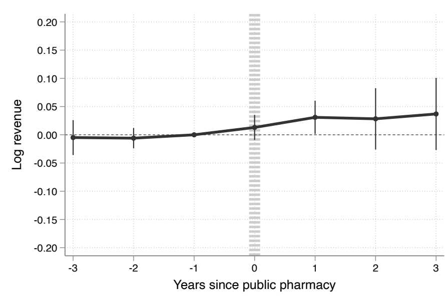
(c) Non-health spending



(d) Non-health revenue



(e) Health spending



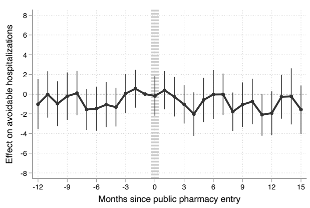
(f) Health revenue

Notes: Spending and revenue are measured in monetary units per capita. Each plot displays results from an event study version of equation (4) given by:

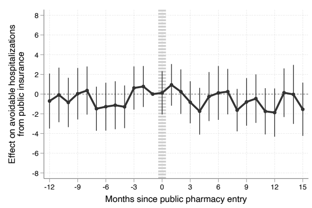
$$y_{ct} = \sum_{k=-3}^{3} \delta_k D_{ct}^k + \theta_c + \lambda_t + \varepsilon_{ct}$$

where the outcomes are the same measures of municipal finance as in Table 5 and treatment dummies are defined as in equation (2). Each dot is coefficient and vertical lines indicate the 95 percent condence intervals.

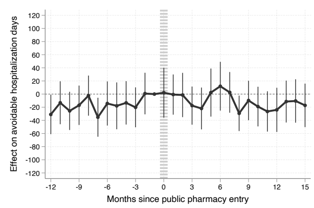
Figure A.12: Event study estimates for effects on avoidable hospitalizations



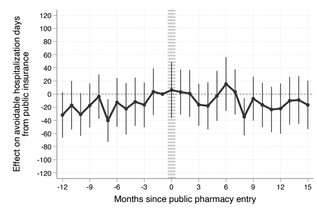
(a) Number of hospitalizations, all insurance



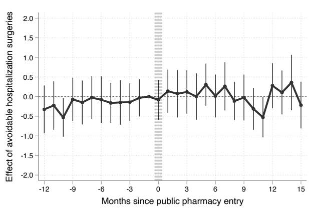
(b) Number of hospitalizations, public insurance



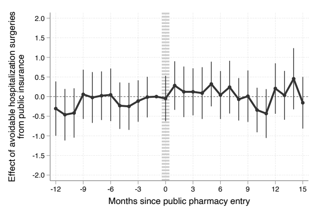
(c) Days of hospitalizations, all insurance



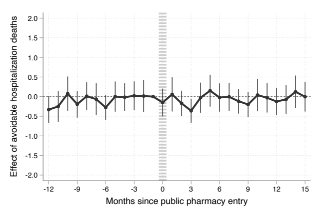
(d) Days of hospitalizations, public insurance



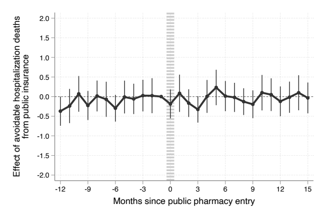
(e) Number of surgeries, all insurance



(f) Number of surgeries, public insurance



(g) Number of deaths, all insurance



(h) Number of deaths, public insurance

Notes: Each plot displays results from an event study version of equation (4) given by:

$$y_{ct} = \sum_{k=-12}^{15} \delta_k D_{ct}^k + \theta_c + \lambda_t + \varepsilon_{ct}$$

where the outcomes are the same measures of avoidable hospitalization events as in Table 6 and treatment dummies are defined as in equation (2). Each dot is coefficient and vertical lines indicate the 95 percent condence intervals.

Table A.1: Within county analysis of public pharmacy entry

Dependent variable: Indicator for the presence of a public pharmacy

	(1)	(2)	(3)	(4)	(5)
	1(Public pharmacy)				
Private pharmacies in 2014	0.021***	0.017***	0.019***	0.019***	0.009***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
Schools in 2010	0.015***	0.013***	0.011***	0.006***	0.002***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Cell size is (in meters):	1,000	800	600	400	200
Cells	22,057	30,231	46,593	90,415	307,318
Mean of dependent variable	0.006	0.004	0.003	0.001	0.0004
Mean of private pharmacies	0.118	0.085	0.055	0.028	0.008
County fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a geographic cell within a county. We use all 147 counties with a public pharmacy operating by December 2018. Private pharmacies are measured in the year 2014, before the opening of public pharmacies. Sample uses only "populated cells," i.e. cells within the convex hull of existing schools. Different columns display results for different definitions of cell size, from 1,000×1,000 meters in column 1 to 200×200 meters in column 5. Standard errors are clustered by county.

Table A.2: Was a treatment delivered?

	(1)	(2)	(3)	(4)
	Delivered	Explained	Content	Useful
Treatment	0.107***	0.238***	0.304***	0.624
	(0.033)	(0.043)	(0.059)	(0.438)
Constant	0.769***	0.440***	0.379***	7.208***
	(0.025)	(0.033)	(0.049)	(0.379)
Observations	514	514	297	191
R-squared	0.020	0.060	0.083	0.011

Notes: This table displays results from different regressions of measures of treatment delivery on indicators for each of the treatment groups. Column (1) uses an indicator for treatment delivery as an outcome; column (2) uses an indicator for a treatment being explained; column (3) an indicator for whether the participant recalls that the treatment was related to public pharmacies, conditional on receiving it; and column (4) a response in a scale from 1 to 10 regarding the usefulness of information, conditional on recalling the content. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Balance in covariates accross attrition status

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Non-Attrites vs Attriters			Panel B: Non-Attriters		
Variable	Non-Attriters	Attriters	p-value $H_0 : (1) = (2)$	Control	Treatment	p-value $H_0 : (4) = (5)$
Age	46.70	44.60	0.09	46.62	46.77	0.62
	(16.67)	(18.08)		(16.84)	(16.57)	
Education higher than HS (=1)	0.53	0.52	0.89	0.54	0.52	0.72
	(0.50)	(0.50)		(0.50)	(0.50)	
Female (=1)	0.64	0.58	0.06	0.62	0.66	0.74
	(0.48)	(0.49)		(0.49)	(0.47)	
Days with internet (0-7)	5.26	5.43	0.40	5.12	5.35	0.37
	(2.84)	(2.71)		(2.92)	(2.78)	
Works (=1)	0.63	0.64	0.74	0.59	0.65	0.82
	(0.48)	(0.48)		(0.49)	(0.48)	
Support for incumbent (=1)	0.48	0.56	0.09	0.50	0.47	0.23
	(0.50)	(0.50)		(0.50)	(0.50)	
Voted in previous election (=1)	0.76	0.70	0.06	0.74	0.78	0.88
	(0.43)	(0.46)		(0.44)	(0.41)	
Knows public pharmacy (=1)	0.67	0.60	0.04	0.64	0.69	0.08
	(0.47)	(0.49)		(0.48)	(0.46)	
Observations	514	312		216	298	

Notes: Columns 1 and 2 display the mean and standard deviation of different covariates at baseline for sample non-attriters and attriters respectively. Column 3 displays the p-value from a test of equality of means across both groups. Columns 4 and 5 display the mean and standard deviation of different covariates at baseline for treatment and control group within the group of non-attriters surveyed at follow-up. Column 6 displays the p-value from a test of equality of means across both groups within the group of non-attriters surveyed at follow-up.

Table A.4: Decomposition of effect on drug prices in the private market

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Average paid price		Price changes ($\hat{P}_{PC}$)		Share changes ($\hat{P}_{RW}$)		Correlation of price and share changes ($\hat{P}_{CS}$)		Drug entry ($\hat{P}_{E}$)		Drug exit ($\hat{P}_{X}$)	
PP index	0.017***		0.011***		-0.004*		0.004***		0.006***		0.000	
	(0.003)		(0.001)		(0.002)		(0.001)		(0.002)		(0.000)	
PP index × chronic (β_C)		0.019***		0.008***		-0.001		0.003**		0.009***		0.000
		(0.003)		(0.002)		(0.002)		(0.001)		(0.003)		(0.000)
PP index × non-chronic (β_{NC})		0.016***		0.015***		-0.007**		0.005***		0.002		0.000
		(0.004)		(0.003)		(0.003)		(0.002)		(0.003)		(0.001)
p-value for H_0: $\beta_C = \beta_{NC}$	-	0.536	-	0.024	-	0.133	-	0.436	-	0.159	-	0.628
Observations	649,885	649,885	649,885	649,885	649,885	649,885	649,885	649,885	649,885	649,885	649,885	649,885
R-squared	0.994	0.994	0.848	0.848	0.789	0.789	0.559	0.559	0.991	0.991	0.837	0.837
Molecule-by-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Molecule-by-Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays estimates of equation (3). The treatment variable is the share of the population in location l exposed to public pharmacies The dependent variables are each of terms in equation (6). In even columns, exposure to the public pharmacy is interacted with an indicator for whether a molecule is targeted towards a chronic condition or not. Standard errors clustered at the molecule-by-location level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Effect on drug sales and prices in the private market

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+sales)			log(price)		
First PP index	-0.039***	-0.041***		0.006**	0.009***	
	(0.011)	(0.005)		(0.003)	(0.001)	
First PP index × chronic (β_C)			-0.054***			0.009***
			(0.006)			(0.001)
First PP index × non-chronic (β_{NC})			-0.023***			0.010***
			(0.008)			(0.002)
p-value for H_0: $\beta_C = \beta_{NC}$	-	-	0.002	-	-	0.527
Observations	681,120	681,120	681,120	649,885	649,885	649,885
R-squared	0.014	0.543	0.544	0.520	0.848	0.848
Molecule FE	Yes	No	No	Yes	No	No
Month FE	Yes	No	No	Yes	No	No
Location FE	Yes	No	No	Yes	No	No
Molecule-by-Month FE	No	Yes	Yes	No	Yes	Yes
Molecule-by-Location FE	No	Yes	Yes	No	Yes	Yes

Notes: This table displays estimates of equation (3). The treatment variable is the share of the population in location l with access to the first public pharmacy when it first became available. In columns 3 and 6, exposure to the first public pharmacy is interacted with an indicator for whether a molecule is targeted towards a chronic condition or not. Standard errors clustered at the molecule-by-location level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.