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

Juan Pablo Atal, *University of Pennsylvania*
José Ignacio Cuesta, *Stanford University*
Felipe González, *Pontificia Universidad Católica de Chile*
Cristóbal Otero, *University of California, Berkeley*

Abstract. We study the market and political aspects of private-public competition leveraging a large-scale and decentralized entry of hundreds of retail public pharmacies in Chile. Exploiting quasi-experimental variation and a field experiment, we show that mayors opened public pharmacies in dense urban areas where private pharmacies operated. Public pharmacies affected the shopping behavior of local consumers by emerging as a low-price and low-quality alternative to private pharmacies, generating market segmentation and price increases in the private sector. This segmentation created winners and losers, as it delivered large benefits for a small share of users and imposed small costs to a large share of non-users. Altogether, public pharmacies increased consumer savings and mayors were politically rewarded in the upcoming election, providing novel evidence of political returns to the introduction of a public option in local markets.

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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, 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). Moreover, state-owned firms may be unfair competition to private firms if they enjoy a competitive advantage by being directly or indirectly subsidized by the government (Martin, 1999). Tackling these questions 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.

This paper contributes to this debate by studying a decentralized and large scale entry of public retail pharmacies in Chile. During the year prior to the 2016 local elections, public pharmacies entered in a third of the counties throughout the country. Public pharmacies emerged as competition from local governments to a fully deregulated and highly concentrated private retail market characterized by high prices.[1] These pharmacies are managed by local governments and sell drugs to people who live in their counties at prices that are, on average, a third of those at their private counterparts. Their ability to offer lower prices comes partly from purchasing through the public intermediary, which gives public pharmacies a cost advantage relative to private pharmacies.

Between 2015 and 2018, public pharmacies entered in 147 of the 345 counties of Chile. The data shows patterns consistent with politics playing an important role in entry decisions. Entry was strongly concentrated in the months before local elections: 86 percent of public pharmacies opened within the year before the elections. We also show evidence that public pharmacies entered mostly in populated and high-income counties. Within counties, public pharmacies located in dense areas were private pharmacies were also operating. We also document that, while attractive in terms of their low prices, public pharmacies were also less convenient in terms of access (they have a single location per county), opening hours, waiting times, and product variety. Overall, public pharmacies are relatively low-price and low-quality competitors to the private sector.

To study the impact of public firms, we combine quasi-experimental approaches with a field experiment. The former exploits the staggered entry of public pharmacies across counties, as we find that the *timing* of entry was unrelated to baseline differences or pre-trends in local market

[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. See OECD (2015) for more details about country comparisons.

attributes. The field experiment was an informational intervention that we randomly provided to a subset of consumers in counties that opened public pharmacies during the weeks before the 2016 local elections. We provided information about the existence, the location, and the positive and negative attributes of public pharmacies. We surveyed both the treatment and control groups before the intervention and two months after it. Our survey included questions about drug shopping behavior and political participation, which we exploit to study the economic and political effects of public firms in our setting.

To understand the role of public firms, we begin by estimating their competitive effects on the local pharmaceutical market. We use our field experiment to estimate the impact of information about the availability of public pharmacies on knowledge and consumer shopping behavior in public pharmacies. We find that our informational treatment shifted self-reported actual and expected shopping at public pharmacies. These effects are concentrated among consumers with household members that suffer chronic conditions, who are exactly the subset of consumers targeted by public pharmacies.

We also find that the entry of public firms impacted market outcomes in the private sector. We exploit detailed 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 is concentrated among drugs targeted towards chronic conditions, which is consistent with our experimental evidence. We also find a growing *positive* effect of public pharmacies on prices in the private sector: By the end of our sample period, the entry of public pharmacies had induced private pharmacies to *increase* their prices by 1.1 percent. The positive price effect suggests that the low-price and low-quality public option generates market segmentation: private pharmacies responded to a shift of price-elastic consumers towards public pharmacies by increasing prices. Overall, these results show that the public option generates winners and losers as a consequence of its equilibrium effects.

We then estimate the effect of public firms on citizens' political support for mayors who opened public pharmacies. We find that consumers—and citizens more broadly—who were more exposed to public pharmacies were significantly more likely to vote for the incumbent mayor running for reelection. Exploiting our informational intervention, we show that awareness about the availability and attributes of a public pharmacy increased the likelihood of supporting the mayor by 6-8 percentage points (p.p) in the upcoming election. Becoming aware of the availability of a public pharmacy locally has a persuasion rate in terms of supporting the mayor of around 4 percent, which is in the range of the estimates in the persuasion literature (DellaVigna and Gentzkow, 2010).

We confirm and complement our experimental evidence of voting behavior with administrative booth-level data covering almost 1.3 million citizens. Our strategy exploits the quasi-random assignment of voters to booths and compare the support for mayors between (i) people who were exposed to a public pharmacy that opened *before* the 2016 election with (ii) people also exposed but in a county where the pharmacy opened *after* the election. Anecdotally, the latter counties experienced unexpected delays in the bureaucratic procedure between processing sanitary permits to open the pharmacy and actually opening it. We show that those counties serve as a valid control group for evaluating the effect of *opening* a pharmacy on voting behavior. This quasi-experimental evidence confirms that public pharmacies entail a political return. The slope of this rewards is quantitatively relevant: a 1-kilometer increase in euclidean distance to the public pharmacy is associated with 5 p.p fewer votes for the incumbent mayor who opened the pharmacy. Similarly, a 10-years increase in the average age of voters in a booth, which increases the likelihood of buying medicines at public pharmacies, is associated with a 1.2 p.p higher vote share of the incumbent mayor.

To put these numbers in context, we estimate that the availability of a public pharmacy generates monthly et. savings of US$28 to consumers with a chronic disease, which we estimate increase their support for the incumbent by 8 p.p in our experiment. For comparison, Manacorda et al. (2011) find that a monthly transfer of US$70 increased the political support of the incumbent by approximately 12 p.p. in Uruguay. Thus, we estimate a political return to public firms that is similar to that of cash transfers.

We finish by studying potential spillover effects of public pharmacies. First, if pharmacies increased access to drugs, then prescription adherence may increase and health outcomes improve. Using detailed data on avoidable hospitalizations and deaths, we find no evidence of spillovers in this dimension. These results are consistent with our finding that public pharmacies did not increase aggregate drug sales in local markets. Second, if municipalities ran their public pharmacies at either profits or losses, then they would have to adjust other non-health services (e.g. education) to meet their budget constraint. Using detailed data on municipal finances, we find that public pharmacies increased both spending and income, with little effects on other (non-health) services. Therefore, public firms can generate consumer savings relative to the private option while being financially sustainable regardless of their political returns. This result is partly explained by the cost advantage held by public pharmacies and the extent of market power held by private pharmacies.

Taken together, our results show that public firms in our context can be characterized as low-price and low-quality competitors. As a consequence we observe market segmentation between public and private firms, which in turn generates winners and losers. Still, mayors are politically rewarded: consumers value public firms, which implies that they are a good policy in the lens of citizens. However, this result also raises concerns related to the potential use of public firms for political purposes.

By analyzing the political and market effects of public pharmacies, we inform the long-standing question of state versus private ownership of firms. A key aspect in this regard are the benefits derived from competition between privately- and publicly-owned 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 public firms in local markets, either directly managed by the 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 the randomized controlled trials by Busso and Galiani (2019) and Banerjee et al. (2019) in the Dominican Republic and Indonesia, respectively. That research 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 on market outcomes, and showing that public firms can induce market segmentation and potentially lead to an increase in prices by private firms.[2]

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 characteristics of candidates in an election, policies that were implemented by the incumbent, 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). The experimental part of our analysis differs from previous research in that we provided information about a specific policy directly to the people most likely to be affected by it and a few weeks before the election. The focus on health makes our paper also related 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 remains 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 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 reduce drug prices, including price regulation (Mohapatra and Chatterjee, 2020), quality regulation (Atal et al.,

[2]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).

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. Of particular policy concern is the low supply in poor or remote neighborhoods, arguably due to lack of incentives for private pharmacies to enter some markets in spite of their positive externalities.[3] By showing that public pharmacies do not enter in pharmacy deserts, we show that decentralized public pharmacies are unlikely to increase geographical access to pharmaceuticals.

The remainder of the paper is organized as follows. Section 2 describes the institutional framework of the Chilean pharmaceutical market and the basic attributes of public pharmacies. Section 3 describes the main dataset, the key elements of our quasi-experimental research designs and our experiment. Then, section 4 discusses our findings for the effects of public effects on market outcome, while section 5 does so for political outcomes. 6 provides evidence on (the lack of) spillover effects of public pharmacies. Finally, Section 7 concludes.

2 The public option in retail pharmaceutical markets

Chileans access pharmaceutical drugs by either buying at private pharmacies, or through public health care providers. The private sector is highly concentrated, health products are expensive, and stores are geographically clustered in relatively rich areas (MINECON, 2013). A recent industry study by the antitrust agency documents that margins for producers and retailers were high, at almost 50 percent and 40 percent respectively during our period of study (Fiscalía Nacional Económica, 2019). The country has one of the highest shares of out-of-pocket over health expenditures among OECD countries. Moreover, pharmaceuticals are the most important item of out-of-pocket health expenditures (OECD, 2015; Benítez et al., 2018).

The public sector provides pharmaceuticals at low out-of-pocket cost for a select list of diseases, mainly through primary healthcare institutions.[4] An important difference between both sectors is the mechanism used to buy products from the laboratories. While the private retailers buy directly from producers, the public sector uses an intermediary to leverage the high demand and obtain lower prices. The goal of public pharmacies was to exploit the intermediary to create a public retail option with cheaper products and offer these to a broader public.

[3]These areas are often called "pharmacy deserts" (see e.g., Qato et al., 2014; Gannaway, 2018). The lack of pharmacies in local markets increases the costs of medication adherence for consumers, and lack of adherence is often associated with increases in health care costs (Cutler and Everett, 2010).

[4]Primary healthcare institutions include health centers, family health centers, health community centers, rural health centers, and primary emergency care. The focus of these institutions is on preventive healthcare.

2.1 Public pharmacies

The first public pharmacy in Chile opened in October of 2015 as a response to a collusion scandal in the pharmaceutical industry. In 2008, the three largest firms, which owned more than 90 percent of the market, colluded to increase the prices of hundreds of health products (Alé, 2017). In a highly publicized case, the National Economic Prosecutor declared pharmacies guilty. As a consequence, citizens demanded local governments to offer health products at lower prices. A left-wing mayor of a large municipality listened to public demands and the first public pharmacy was born.[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 2018, 147 out of the 345 municipalities in the country were operating a public pharmacy. Figure 3 plots the number of municipalities with a public pharmacy over time.

Public pharmacies are able to offer products at lower prices than their private counterparts partly because they acquire products through a public intermediary that operates under the umbrella of the Ministry of Health called National Supply Center (*Central Nacional de Abastecimiento*, CENABAST). This intermediary receives periodic orders from public healthcare facilities and negotiates on their behalf. By exploiting the large demand from the public sector in a bidding process, the intermediary is able to obtain lower prices than private pharmacies.[6] Without the intermediary, public institutions would have to buy products directly from laboratories at a potentially higher price.[7] 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 4.1.1, public pharmacies offer prices that are on average around a third of the price in private pharmacies, although discounts vary considerably across drugs. Price differences are larger for branded than generic drugs, given that the former are substantially more expensive in private pharmacies (Atal et al., 2019).

The population that benefits from public pharmacies are consumers who live in places where a public pharmacy operates. There are, however, three relevant aspects to consider. First, consumers can only buy at these pharmacies if they meet certain requirements. The vast majority of public pharmacies—approximately 80 percent in the capital—require consumers to reside in the same municipality where the pharmacy operates. To prove residency, consumers must provide a utility

[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 (Jadue, 2015). According to the latest political polls, he is the leading presidential candidate for the upcoming election.

[6]On average, private pharmacies pay 70% more than the public intermediary for the same product (Fiscalía Nacional Económica, 2019).

[7]In some cases, the intermediary is unable to acquire some products, in which case public pharmacies buy directly from producers and a few use subsidies to reduce the final price paid by consumers (see Filún (2018)). Also, some municipalities are restricted from using the intermediary due to outstanding debts with the institution.

bill with their name and home address, so this is a fairly low cost constraint. The remaining 20 percent of pharmacies require consumers to either reside, study, or work within the boundaries of the municipality.[8] Second, the exact location of public pharmacies is important as these need to operate geographically close to consumers for it to be a real alternative. In the following section we show that there is a single public pharmacy per county and most opened in dense urban areas where private pharmacies operated. Third, opening hours might be inconvenient for some consumers, particularly given the fact that there is always at least one private pharmacy operating and public pharmacies operate only in restricted hours in week days.

2.2 Political and economic controversies

The increasing popularity of public pharmacies has been surrounded by significant economic and political controversies. On the economics side, there are two main critiques. First, these pharmacies might be financially unsustainable and therefore could represent a burden for local governments. This argument may have some basis, particularly if municipalities are relying heavily on subsidies instead of the public intermediary. Second, pharmacies could be a source of unfair competition in the market, especially for small private pharmacies that represent approximately 10 percent of the market and were not involved in the collusion scandal. While we do not take a stand on the normative aspects of these critiques, the positive ones motivate some of our analysis, particularly the impact of public pharmacies on the private sector and on the municipal finances.

On the political side, critics have expressed concern about the use of these pharmacies for electoral purposes. Their opening before the local election in October 23, 2016 in which incumbent mayors were running for a reelection seemed far from a coincidence for many. Figure 3 shows that the opening of these pharmacies exploited in the months before these local elections and came to a sudden stop immediately after the vote, creating a bunching of inaugurations that is hard to explain without resorting to a political argument. In fact, some politicians have called public pharmacies "left-wing populism" (*Publimetro*, November 2015), complained about their use "for political purposes" (*La Tercera, August 2016*), and emphasized that they were "politically profitable"(*El Mercurio*, April 2017). If pharmacies were used by mayors to get reelected or affected their evaluation are open questions that motivate part of our empirical analysis.

[8] We take this constraint into account when designing our field experiment by sampling consumers of private pharmacies that operate close to a public pharmacy. More details in Section 3.4.

3 Data collection and descriptive statistics

This section describes the data we use to measure the pharmaceutical market, local elections, and the entry of public pharmacies. We also present our field experiment designed to measure changes in the decisions of consumers after learning about the existence of a public option in this market.

3.1 The pharmaceutical market

Public pharmacies. We collected the opening dates of public pharmacies using two sources. First, we appealed to a recent transparency law that mandates public institutions to deliver information about their operations. Because public pharmacies buy pharmaceuticals using regional health institutions, the state has information about their opening dates. However, some dates were not delivered and others corresponded to the requests of permits to open the pharmacy. Hence, we complemented this information with regional newspapers containing the (big) local news of a public pharmacy opening in town. Figure 3 plots the total number of public pharmacies operating over time. In addition to opening dates, we also geocoded the location of pharmacies and hand-collected prices of the pharmaceuticals they sell using data from newspapers, media articles, and the (few) websites of some pharmacies.

Regarding the supply of drugs by public pharmacies, we only have access to data for those the 96 pharmacies that purchase drugs through CENABAST. For that sample, we have access to transaction-level data that records the name, molecule, dosage, amount, and price of every individual drug purchased by public pharmacies between in 2016–2018. We describe these data in section 4.1.1, where we contrast prices, quantities and variety by public pharmacies to those in private pharmacies. A limitation of this dataset is it only reports purchase prices, but not retail prices by public pharmacies. However, given public pharmacies are not for-profit and charge small or no margins, these data are nevertheless informative.

Private pharmacies. Data measuring the functioning of private pharmacies comes from International Market Statistics (IMS) Health Chile. These data contain monthly drug prices and sales across the market for 2014–2018. IMS collects data from two sources. The four largest pharmacy chains in the country, accounting for more than 90 percent of drugs sold in Chile, report retail prices and sales directly to IMS. Sales from other pharmacies are supplied by wholesalers, which report wholesale prices and sales to IMS, which translates them to retail prices using a standardized method.[9] We employ monthly sales and prices from all 83 local markets included in the IMS

[9]This method consists of adding a value-added tax of 19 percent and a retail margin of 30 percent. We adjust these retail prices in two ways. First, we transform nominal prices to real prices in 2013 using the health CPI from the

data, which cover most of the urban areas of the country. The IMS data set 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. 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. To measure local politics we use three administrative data sets from the Electoral Service. The first dataset contains county-level information about candidates, parties, coalitions of parties, and votes by candidate in the 2012 and 2016 local elections. We use the 2012 election to characterize the political equilibrium before the opening of public pharmacies. In particular, for each county we construct the number of competitors, the winning margin, the vote share of the winner, and identify the winners.

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 declare to live, 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 approximately 42,000 booths in the data.

We construct the third dataset using the electoral registry. For each one of the more than 14 million people in the roll we observe their self reported home address, their gender, and a proxy of their age based on their national ID number. As consumers usually purchase drugs in pharmacies close to their homes, we construct a measure of booth-level exposure to public pharmacies using home addresses. We sample booths and people from counties with a public pharmacy.[10] The sampling proceeds as follows. In the first step, 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 people per booth. Then, we geocode the home addresses of 100,000 people in almost 4,000 booths. In the final step, we collapse the person-level data to the booth-level with the following booth-level variables: the percentage of women, the average age, the distance from voter homes to the public pharmacy and to the county hall, and the distance from the booth to the public

National Institute of Statistics (*Instituto Nacional de Estadística*, INE). Second, we normalize drug prices across drug presentations by their drug content by calculating prices per gram of the active ingredient.

[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.

pharmacy and the county hall.

3.3 The entry of public pharmacies

Public pharmacies were opened by mayors and therefore we can study their decisions using data. To characterize the entry of the public option locally, we use county-level data with information on the pharmaceutical market (IMS), public health (Public Health Institute), and socioeconomic characteristics of the population (National Socioeconomic Characterization Survey). We begin with a characterization of mayors that decided to open a public pharmacy. We then move to study *when* to enter and *where* to open within the county. We argue that, although the decision to open a public pharmacy depends on a wide range of factors, when to enter is more fortuitous and depends, among others, on the time it takes to process the necessary sanitary permits.

Columns 1, 4, and 5 in Table 1 present differences across counties with and without public pharmacies. The upper panel shows that counties with public pharmacies had significantly *more* private pharmacies per 100,000 inhabitants (13.6 versus 7.7, p-value<0.01). This table also reveals that public pharmacies opened in dense high-income counties with people who had more private health insurance, better health, and with a pharmaceutical market with 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 (less) likely to have a winner from the left-wing (right-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 seems more fortuitous. Columns 2 and 3 in Table 1 compare the characteristics of counties that opened public pharmacies before the 2016 election with counties that opened them after the election. In contrast to the previous comparison, all differences are now significantly smaller in terms of economic magnitude and these are also not statistically significant at conventional levels. Moreover, results in column 7 show that pharmacies opening earlier entered similar pharmaceutical markets than those opening later on. To examine the timing of entry more systematically, we ranked all public pharmacies by their entry date, from 1 to 147. Then, we estimated an ordered logit regression for this ranking on all variables in Table 1. Pharmacies opening earlier entered counties with more population and are more likely to be run by left-wing mayors, but the timing of entry among them is uncorrelated with most characteristics of the pharmaceutical market and it is also uncorrelated with electoral competitiveness in the previous election. In our analysis, we rely on these results to compare counties that opened right before with those that opened right after the elections as a valid research design.

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 decisions empirically, we geocoded all public and private pharmacies in the country and constructed geographic cells of 600×600 meters. We then estimated cross-sectional regressions using cells only from counties with a public pharmacy. The dependent variable is an indicator that takes the value of one for cells with public pharmacies and the main explanatory variables are the number of private pharmacies, the number of schools (population proxy), and county-level fixed effects to estimate within county decisions. Table A.1 presents results. The estimates reveal that public pharmacies opened in populated areas where private pharmacies operated already. The maps in Figure 1 provide visual examples of the entry decision in the two largest conurbations of the country. These patterns are in stark contrast with the idea of public pharmacies covering pharmacy deserts.[11]

3.4 The informational 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 where it was revealed that consumers were uninformed in two dimensions. First, some households were unaware of the existence of a public pharmacy. Second, even when households knew about the pharmacy, they were uninformed about the lower prices. Search costs might deter households from using public pharmacies.

The treatment consisted of an informational flyer, displayed in Figure 2-A and 2-B. One component provided information about the existence of a public pharmacy in the county, and stated that the public pharmacy offered lower prices and longer waiting times to receive products than private pharmacies. The second component included detailed location and contact information, hours of attention, and eligibility requirements. We delivered the flyer to people coming out of private pharmacies (i.e. consumers) in the 20 counties with public pharmacies in the Santiago metropolitan area, as displayed in Figure A.1. To strengthen the relevance of the flyer, the information was tailored to the context of each county.

To select participants we hired college students as enumerators. In each county, enumerators approached consumers leaving a private pharmacy and assessed their eligibility. If eligible, the customer was asked to participate and, upon informed consent, the enumerator would proceed to collect a baseline survey. Eligible participants were those who (i) resided and were registered to vote in the county, and (ii) had purchased a prescription drug, and (iii) were not registered in the public pharmacy. The second requirement is important since these are the only drugs sold

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

by public pharmacies. Overall, 1,855 people were approached and 826 accepted to take part of the study. The baseline survey collected information on their awareness of public pharmacies and their attributes, their intention to vote for the incumbent mayor in the upcoming election, their age, education, and access to internet, among others. Once the survey was completed, participants were randomly allocated to treatment and control groups. The assignment was implemented using a random number generator within the surveying device. We implemented this survey between October 12 and 20, 2016, right before mayor elections. Figure A.2 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 than in the baseline. Additionally, we collected information about their relationship with the public pharmacy in their county. Exploiting contact information collected at baseline, we implemented this survey by phone. We were able to contact and complete the survey for 514 participants, almost two thirds of the baseline sample.[12] In addition, this survey also verified the delivery of the treatment. Table A.2 shows that the treatment group acknowledge having received information more often than individuals in the control group and treated subjects recall public pharmacies being the core of the information content almost twice as often than those in the control group.

Table 2 compares baseline variables across groups. Participants are on average 45 years old and 61 percent are females. More than 60 percent work and most use internet frequently. Half of 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 almost all variables are balanced across groups. The exception is awareness of the public pharmacy so we control for it in the analysis.

4 Market effects of public pharmacies

The introduction of public pharmacies provided consumers in those local markets with an additional alternative for purchasing drugs. In this section, we study the implications of this introduction for market outcomes. We start by describing their direct effects. Then, we estimate their effects on outcomes in the private market. Finally, we study whether aggregate sales in the market were affected by public pharmacies.

[12]Table A.3 assesses the effects of attrition. Panel A shows that attrition is higher among younger participants, males, with a higher support for the incumbent, with less turnout in the last election, and with a 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.

4.1 Direct effects: Prices, quality and shopping behavior

4.1.1 Descriptive evidence

When public pharmacies opened in some local markets, consumers had access to an additional alternative in their choice set which differed from available options in different dimensions. We describe this newly available option by using transaction-level data on the universe of purchases by public pharmacies to the public intermediary CENABAST during 2016–2018. Despite its advantages, these data have the limitation that it cover only 96 of the 147 counties that introduce a public pharmacy during our sample period, see section 2.1 for details.

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 substitute to public pharmacies in local markets in which they open.

Consumers must trade-off lower prices with lower convenience of public pharmacies. In fact, the number of drug varieties is much lower in public pharmacies. Figure 4-b shows that the average number of drugs is 2.2 and 70 percent of molecule-counties offer three varieties or less, while the average number of varieties in private pharmacies is 15.2. Relatedly, Figure 4-c shows that public pharmacies are more likely to offer either only generic drugs or only branded drugs within a molecule: the share of molecule-counties where this happens is 72 percent at public pharmacies and 36 percent at private pharmacies. Moreover, the average market share of generic drugs across molecule-counties is 48 percent at public and 42 percent at private pharmacies. To the extent that consumer value product variety in this market, 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 2.1 exacerbate this attribute of public pharmacies. Furthermore, the average consumer faces a longer travel distance to public pharmacies, given each county has a single public pharmacy but as many as 15.3 private pharmacies on average.

The relevance of public pharmacies in the market has grown over time, reflecting that at least a share of consumers value lower drug prices relative to lower convenience enough to switch to public pharmacies. Figure 4-d shows that their unconditional 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 decrease sales by private pharmacies or rather expand market size. To inform this margin, we estimate the effects of public pharmacies on private pharmacies sales in section 4.2

and on aggregate sales in section 4.3 below.

4.1.2 Experimental evidence

Our experiment provided consumers with information on the availability of public pharmacies as a new alternative to access affordable drugs in their local market. We now study whether consumers learned about the availability of public pharmacies and its attributes and whether knowing about such alternative changed their shopping behavior in the short term. The estimating equation is:

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

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 treatment effects on knowledge about public pharmacies. Columns 1-3 shows that information increased awareness about the availability of the public pharmacy by 6 p.p., from a baseline level of 82 percent. Moreover, columns 4-5 present evidence that information shifted consumer perceptions about drug prices at public pharmacies, which is their most salient attribute as mentioned in Section 2. In particular, perceived prices at public pharmacies decreased by 9 percent as a result of our informational intervention. We also find that perceived waiting time for receiving drugs at the public pharmacy increased, such that they learnt about the main disadvantage of public pharmacies relative to private pharmacies. In particular, consumers' perceived waiting time increased by 20 percent.[13] 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 and become available.

Consumers also react in terms of shopping behavior after becoming informed about public pharmacies. Table 3-B displays estimates of treatment effects using linear probability models for the decision to subscribe, the decision to purchase, and the plan to use the pharmacy in the future, respectively. Although the estimates are noisy, they are positive and economically meaningful. The estimates in column 2 indicate a 2 p.p increase in enrollment on public pharmacies by treated

[13] 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.

households, which is almost a 30 percent increase relative to the mean of the control group. The effect in column 5 implies a 2.3 p.p increase in purchasing in public pharmacies by treated households, more than an 80 percent increase relative to a baseline share of 2.8 percent of households in the control group. Finally, column 8 shows that our intervention increased the rate at which households plan to use the public pharmacy in the future by around 5 p.p., as much as 10 percent relative to a baseline probability of 0.54 in the control group.

Households with members that suffer chronic conditions tend to react more strongly to the treatment. Columns 3, 6, and 9 provide separate treatment effects for households with and without a member that suffers a chronic condition. All treatment effects are larger in magnitude 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 shop periodically for drugs and, thus, the group for which short term effects are more likely to be detectable within our experimental design. Moreover, public pharmacies in many cases prioritize the provision of drugs treating chronic conditions, and thus information about them might be less relevant for consumers without any household member with a chronic condition. Consistent with the latter, estimated treatment effects on consumers without a household member with a chronic condition are close to zero across outcomes.[14]

These results suggest that as public pharmacies enter local markets, consumers become aware of their entry, 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.

4.2 Indirect effects: Prices and sales by private pharmacies

The entry of public pharmacies may push consumers to substitute away from private pharmacies. Moreover, the increased competitive pressure from public pharmacies may induce private pharmacies to adjust drug prices. In this section, we exploit detailed data on drug sales and prices from IMS Health to measure these effects of the entry of public pharmacies.

[14] Again, 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.

4.2.1 Event study evidence

We start by exploiting the staggered entry of public pharmacies in an event study framework. We observe monthly prices and sales between January 2014 and December 2018 at the level of 66 geographic locations l defined by IMS Health. We define markets as the combination of a location l, month t, and molecule m. A challenge for combining data on entry of public pharmacies with data on market outcomes from IMS Health is that the level of geographic aggregation of the latter l is in some cases larger than counties, which is the level at which public pharmacies operate. For these results, we define entry events as the opening of the first public pharmacy among the set of counties that define a location, and later assess the robustness of our results to alternative definitions of entry.

The main specification we study takes the form of an event study:

$$y_{mlt} = \sum_{k=-12}^{15} \beta_k D_{lt}^k + \lambda_{mt} + \theta_{ml} + \varepsilon_{mlt} \tag{2}$$

where the dependent variable y_{mlt} is either logged drug prices or logged drug sales.[15] The main covariate of interest is a vector of dummies $D_{lt}^k = 1\{t = e_{lt} + k\}$ which indicate whether a month t is exactly k months after event time e_{lt} for location l. We normalize the coefficient $\beta_{k=-1} = 0$. Therefore, we interpret all coefficients β_k as the effect of a public pharmacy opening on the dependent variable for each month k relative to the month before the entry event. The specification also includes molecule-month fixed effects λ_{mt} to account for time varying unobservables at the level of molecules, and molecule-location fixed effects θ_{ml} to account for persistent differences in market conditions across locations. Standard errors are clustered at the molecule-location level.[16]

The entry of public pharmacies had meaningful effects on private pharmacies in local markets.

[15] 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 with active ingredient m in location l, P_{ilt} is the logarithm of 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 solely 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 (see e.g. Atal et al., 2019). In the case of 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).

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

Figures 5-a and 5-b present results for drug sales and prices, respectively. Drug sales by private pharmacies decrease after a public pharmacy enters a location. Our estimates imply that after 18 months of the entry of a public pharmacy, private pharmacies in that local market sell around 4 percent less drugs. Furthermore, drug prices in private pharmacies increase after a public pharmacy enters, with an effect of 1 percent after 18 months of the entry of a public pharmacy.[17] Both effects increase over time, suggesting that public pharmacies evolve in terms of enrolling more consumers and improving its product offerings and convenience.

The main threat to the identification of the effect of the entry 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.[18] Reassuringly, the lack of pre-trends in both sales and prices leading to the entry of public pharmacies consistent with the fact that reverse causality and strategic considerations do not play a significant role our setting.[19]

Robustness checks. We provide results for alternative specifications of this event study analysis in Appendix A.1. A first concern with the evidence above comes from how events are defined. We consider an alternative definition of the event, by which we focus on the entry of a public pharmacy to the *largest* municipality in a location as the relevant event for each location. A second concern with our empirical strategy is that it does not take into account that some locations may have multiple events, since different counties within l may introduce public pharmacies at different points in time. To deal with this concern, we follow Lafortune et al. (2018) and stack as many copies of the data as the number of events per location, so we can consider all events in our regression. In both cases, results are quantitatively consistent with our prior findings.

[17] There is little cross-sectional variation in drug prices across locations, which is in line with an empirical fact about retail pricing also documented in other contexts (e.g., Adams and Williams, 2019; DellaVigna and Gentzkow, 2019) which 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 locations, and therefore any widespread price effects across locations are not captured by our empirical strategy.

[18] Although strategic entry is a well known identification threat for reduced form models of market outcomes as a function of firm entry as in equation (2), it is not a relevant concern in our context. Public pharmacies business model differs from those of private pharmacies, and they do not operate for-profit businesses. Furthermore, some of the operation is subsidized by local governments.

[19] As an additional piece of supporting evidence, in column 7 of Table 1 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.

4.2.2 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 location 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 across local markets size. 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 drug prices by private pharmacies by 1.1 percent.[20,21]

The effects of public pharmacies on private pharmacy sales are stronger in molecules associated with chronic conditions. Column 3 in Table 4 shows that the decrease in sales reaches 5.4 percent among such molecules, whereas it is only of 2 percent in molecules associated with non-chronic conditions. This finding is consistent with the fact that public pharmacies mostly focus on drugs related to chronic conditions. Moreover, it is consistent with the stronger effects we estimate in our experiment for how households with member with chronic conditions react more strongly to 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.

[20]The fact that the event study results and these results are quantitatively similar comes from the fact that events are not too dispersed over time, such that the 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 unchanged relative to our baseline results.

[21]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. We find that average paid log 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.

4.2.3 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 this increased price competition could have induced private pharmacies to reduce drug prices, we actually document the opposite: private pharmacies increased drug prices in response to entry by public pharmacies. This response is consistent with consumer 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 thus do not switch. Private pharmacies internalize this change in their pool of consumers and optimally respond to such segmentation by increasing drug prices as their demand becomes more inelastic.[22]

The sales response to the entry of public pharmacies may seem somewhat small given the magnitude of the price differences we have documented between public and private pharmacies. First, our interpretation is that product differentiation plays an important role in mediating this response. As documented above, public pharmacies are less convenient in terms of waiting times, opening hours, product variety, and travel distance than private pharmacies. The lack of a stronger response likely suggests that a sizable share of consumers value those attributes enough as not to substitute towards public pharmacies on the basis of lower prices. A higher quality of the latter would have likely led to stronger equilibrium responses. Second, notice from our event study evidence in Figure 5 that both quantity and price effect increase over time, suggesting that the total effects once the market settles on a new equilibrium may end up being 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). However, they find a decrease in prices, as opposed to the price increase that we document for the private market. Our results highlight that the price effects of public competition will likely depend on the underlying preferences and on the attributes of firms in the market. A natural question then is how do public pharmacies choose their quality. While beyond the scope of this paper, one hypothesis motivated by our results on political effects in section 5 would be that the marginal political returns to quality diminish fast whereas its marginal costs increase steeply, leading to low quality being optimal for mayors seeking reelection.

[22]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".

4.3 Aggregate effects on drug sales

[RESULTS PENDING]

5 Political effects of public pharmacies

This section estimates the impact of the public pharmacies on the political support obtained by the incumbent mayor who ran for reelection. Given that these pharmacies were *not* randomly allocated across counties, we use two sources of exogenous within-county variation to approximate the ideal experiment. First, we use our field experiment around the 2016 local elections to estimate the causal effect of providing information about the pharmacy on self-reported voting in our follow-up survey, implemented shortly after the election. Second, we develop a spatial differences-in-differences design using voting booths which exploits the proximity of voters to the public pharmacy *and* pharmacy entry before and right after the election. Taken together, both econometric strategies suggest that voters rewarded mayors for the opening of public pharmacies.

5.1 Experimental evidence

Our baseline survey, implemented less than a month before the 2016 election, asked about the intention to vote for the mayor in the upcoming local election. Similarly, our follow-up survey asked if the person had voted for the mayor in the election held just a few weeks ago. 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 umbrella of the same political party of the incumbent mayor. We use both surveys and the randomized provision of information to estimate the causal effect of awareness of public pharmacies among consumers in the pharmaceutical market on political support for the incumbent mayor or party.

Table 5 presents estimation results of equation (1) for political outcomes. Columns 1-3 present estimates of the information on an indicator that takes the value of one if the person responded to have voted for the incumbent mayor. Columns 4-6 use a similar indicator for those who responded that they voted for the incumbent political party. The latter does not only include voting for the incumbent mayor, but also voting for the politically closest candidate in the case when the mayor did not run for reelection. In both cases we present results from three specifications: (i) a simple comparison of means across treatment and control groups, (ii) the analogue specification but including a vector of controls, and (iii) the controlled specification but allowing for heterogeneous responses across individuals with and without a chronic condition.

Columns 1 and 3 reveal the percentage of people who reported to vote for the incumbent in the treatment and control groups. Approximately 26-28 percent of people in the control group reported voting for the incumbent, a number that increases by approximately 6 p.p. in the treatment group. Despite the politically relevant magnitude, the higher vote share for the incumbent is *not* statistically significant at conventional levels with p-values of 0.21 and 0.12 respectively. With the goal of increasing the precision of the analysis, columns 2 and 4 include an additional control for the intention to vote for the mayor *before* the intervention and county fixed effects. Moreover, we also include individual-level controls such as age, an indicators for people with a chronic condition, high-school completion, gender, and public insurance. As a consequence, standard errors decrease and the point estimate remains similar at around 6-7 p.p and becomes marginally significant with p-values of 0.06 and 0.11 respectively.[23]

Columns 3 and 6 show that the impact of information is somewhat larger for individuals who reported having a household member with a chronic condition. More precisely, those who live with someone with a chronic condition reported to have voted 8 percentage points more for the incumbent, more than the 2-7 p.p higher vote share in the treated group without a chronic condition. Although the small sample prevent us from rejecting the null of a similar impact across these groups, with p-values of 0.88 and 0.41 respectively, the result is consistent with the the hypothesis that people most affected by the policy are more likely to support the incumbent. 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 acquiring information about the public pharmacies and its characteristics influenced consumers in this market to support the incumbent mayor. [24]

To better understand these effects we calculate the implied persuasion rate (Enikolopov et al., 2011). In this 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. This is, 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 approximately 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 (Enikolopov

[23]To account for the effects of attrition, Table 5 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.

[24]A potential concern with Table 6 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.3 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.

et al., 2011) and political campaigns in dictatorship (González and Prem, 2018), but similar to the persuasion of Fox News (DellaVigna and Kaplan, 2007).[25]

5.2 Quasi-experimental evidence

How do citizens more broadly—instead of just consumers—evaluate public pharmacies? 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, the quasi-random assignment of citizens to booths within counties, which creates booth-level variation in the proximity of voters' *homes* to the public pharmacy and voters' age. We use the age of voters as a proxy for having a chronic disease and thus the probability of using the public pharmacy.[26] Second, we use the opening date of pharmacies. Some opened *before* the elections and some began operating *after*. Anecdotally, it seems that pharmacies opening after the elections were planning to opening before but the necessary sanitary permit took more time than expected. The use of booths in counties where a public pharmacy opened *after* the election allows us to control for the geographic sorting of citizens with different political preferences. Table 1 suggests this comparison is appropriate: counties where public pharmacies opened before are similar to counties where pharmacies opened after the election.

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

$$v_{ijc} = \beta_1(D_{ijc} \cdot O_c) + \beta_2(X_i \cdot O_c) + \gamma_1 D_{ijc} + \gamma_2 X_i + \phi_c + \epsilon_{ijc} \quad (4)$$

where v_{ijc} is an outcome in booth i, located in polling place j, and county c. We use two outcomes, turnout and vote shares for the incumbent. The variable of interest in the vector D_{ijc} is the average distance from the home of voters in booth i to the public pharmacy operating in county c (in km.). This vector also includes the distance from the polling place (j) to the public pharmacy (c) and the distance from voter homes (i) to the city hall (c) respectively. The indicator O_c takes the value of one in counties where public pharmacies opened *before* the 2016 elections. The vector X_i represents the characteristics of voters in booth i, namely the share of female voters and the average age of voters. Finally, ϕ_c is a set of county fixed effects, and ϵ_{ijc} is an error term correlated within counties. The parameters of interest are β_1 and β_2, which measure the differential voting behav-

[25] Figure A.7 provides more details about these comparisons. DellaVigna and Gentzkow (2010) provide an early review of the empirical evidence on persuasion rates.

[26] Panel (a) in Figure A.8 reveals that few people younger than 30 years old take medicines to treat a potential chronic disease, a number that increase rapidly with age. As expected, panel (b) in this figure shows that the distribution of voters' age across booths in counties with pharmacies that opened before and after the election is similar.

ior of individuals who lived close to a public pharmacy that opened before the elections—those who were more exposed geographically—, and the voting behavior of relatively old individuals in counties where the public pharmacy opened before—those who were more expesed because of their higher likelihood of using the public pharmacy.[27]

Table 6 presents estimates of equation (4). Column 1 shows that the when a voter's home is closer to the public pharmacy, then the vote share of the incumbent coalition in power is higher relatively to those who live farther. In particular, the coefficient implies that a 1-kilometer increase in the distance to the public pharmacy is associated with 5 p.p. fewer votes for the incumbent coalition in power, 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. We find that a 10-year increase in the average age of voters in a booth, an increase of approximately 1 standard deviation, is associated with a higher vote share for the incumbent of 1.2 p.p. 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. Table A.6 shows the results are similar if we use the logarithm of distances. These estimates are consistent with a higher exposure to the pharmacy bringing more votes to the incumbent mayor and are consistent with previous experimental estimates.

The results suggest that public pharmacies increased the vote share of incumbent mayors. Although the two strategies approximate the ideal experiment in which pharmacies are randomly allocated across counties, note that both are threatened by a potential unobserved impact of pharmacies in the group that acts as the counterfactual. 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. The existence of some information in the baseline makes our estimates a lower bound among consumers in the pharmaceutical market. Similarly, in the quasi-experimental design voters could have rewarded the mayor for the (expected) future opening of the pharmacy. If this is the case, then the control group also supported the mayor and our estimates constitute a lower bound.[28]

[27]We allow voters who live close to the pharmacy to differ in unobserved variables that also affect voting patterns through the inclusion of D_{ijc}. In addition, we are also controlling for the effect of public pharmacies located in the city hall. Among the 141 pharmacies in these data we observe 20 operating inside this building. However, we can control for this potential confound by including in the regression the distance from voters' home to this building d_{ic}.

[28]Yet another possibility is that voters expected the pharmacy to open before rather than after the election and thus punished the incumbent mayor for the delay, which would make our estimates an upper (instead of a lower) bound. Although theoretically possible, we find little anecdotal evidence of this being the case. Moreover, the field experiment shows that information about pharmacies increased support for the mayor and thus the punishment would have to be as large as the reward to make our estimates insignificant, which we find unlikely to be the case.

5.3 The political returns of consumer savings

Consider a back-of-the-envelope calculation that combines the market and political effects to estimate the amount of consumer savings necessary to generate one vote. Consider that the average municipality with a public pharmacy hosts 100,000 people and 22 percent treat their chronic disease regularly using medicines according to the 2016–2017 National health Survey. Thus the maximum number of people that can be served by public pharmacies is 22,000. From our surveys we know that consumers with a chronic disease spend US$70 per month on drugs, hence the local pharmaceutical market has sales for US$1.5 million. We estimated that public pharmacies stole 4 percent of the market share without attracting new consumers to the market. Therefore, public pharmacies have sales of about US$60,000 monthly. Given that 5% of the county is enrolled in a public pharmacy (Filún, 2018), the average public pharmacy serves 5,000 consumers who spend and average of US$12. As the public pharmacy sells medicines with a 70 percent discount, we calculate that 43 percent of the spending of the switchers remains in the private pharmacy.

Consumers decrease their out-of-pocket spending in medicines, but there are winners and losers. The losers are those who remain buying drugs from private pharmacies at higher prices. Given that prices increased by 1 percent, spending on drugs by this group increased by US$12,000 monthly ($0.01 \times 70 \times 17000$). At the same time, the switchers are the winners and save US$60,000 monthly ($0.3 \times 0.57 \times 70 \times 5000$). However, they also lose US$1,500 for the higher prices of the drugs they still buy at the private pharmacy. When added up, consumers who switched save US$58,500 and the net benefit for consumers is then US$46,500 monthly. Using the experimental results we calculate that because of the pharmacy the mayor got 1,120 additional votes and thus 1 additional vote per US$42 of monthly consumer savings.[29]

We can also compare the political return of public pharmacies with the impact of cash transfers. Consumers who switched to the public pharmacy save an average of US$28 monthly. Then, the public pharmacy can be interpreted as a monthly cash transfer of US$28 targeted to consumers with a chronic disease. We find that this "transfer" increased political support for the incumbent mayor by 8 p.p. For reference, Manacorda et al. (2011) find that a targeted monthly transfer of US$70 increased the political support of the incumbent government by 11 p.p. in Uruguay. Assuming linearity we calculate that a cash transfer of US$70 targeted to regular consumers with a chronic disease would increase support for the incumbent by 12 p.p. Thus, we calculate a political return that is similar to the political impact of targeted cash transfers.

[29] According to data from the 2012 elections, there are 23,000 voters in the average municipality and our estimates suggest that public pharmacies had little effects on turnout but increased votes for the incumbent mayor. The calculation is $0.04\times(0.78\times23000)+0.08\times(0.22\times23000)=1120$ where the first term represents the additional support among voters without a chronic disease and the second the change in votes among voters with a chronic disease. We are implicitly assuming the same distribution of chronic diseases within the population of voters and non-voters.

6 Spillover effects of public pharmacies

Public pharmacies may have effects beyond the pharmaceutical market and political outcomes. In this section, we explore two such potential spillovers. First, we explore whether changes in access to the pharmaceutical stem to broader effects on health outcomes. Second, we study whether other components of municipal finance are affected by the expenses associated to introduction of public pharmacies.

6.1 Health outcomes

A prominent aspect on which improved access to pharmaceutical drugs could benefit households is their health. A mechanism for such effects would be improved adherence to prescription drugs for individuals with chronic diseases due to lower prices and increases access (Cutler and Everett, 2010). However, in our setting we do not observe individual level prescriptions and consumption of drugs. Instead, we focus on avoidable hospitalizations associated to chronic diseases, which would have likely not occurred under appropriate disease management. This is a variable that 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 appealing for this setting. We would interpret a decrease in avoidable hospitalizations in a county where a public pharmacy entered as a signal that increased the pharmacy increased access to pharmaceutical drugs and, in consequence, prescription adherence by individuals with chronic diseases.

For this analysis, we estimate the following regression:

$$y_{ct} = \beta PP_{ct} + \theta_c + \lambda_t + \varepsilon_{ct} \tag{5}$$

where y_{ct} is a hospitalization outcome in county c and month t, and PP_{ct} indicates the period after the entry of a public pharmacy in county c. The specification includes county and month fixed effects. To construct the outcome variable, we exploit data on monthly hospitalization outcomes for 2013–2018 from public records collected by the Ministry of Health (DEIS, 2019), which cover number of hospitalizations, days of hospitalization, number of surgeries, and number of deaths across all hospitals in Chile per diagnosis. The number of hospitalizations captures only the volume of these events, whereas hospitalization days, and deaths additionally 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 county population and measure them per 100,000 inhabitants.

Our estimates provide no evidence that public pharmacies improved health outcomes, at least as measured by avoidable hospitalizations. Table 7-A displays the main results from this analysis. For each outcome, we first show results for all households in the county and then for households 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 the possibility of effects that could be quantitatively meaningful. In particular, for the full population 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 a reduction of between 4 and 7 percent in these outcomes relative to their baseline levels.

Figure A.9 presents estimates from and event study version of equation (5). For all outcomes and samples, we again find no evidence that public pharmacies affected health outcomes of local consumers. Reassuringly, these results show a lack of differential trends across counties leading to the entry of public pharmacies, which provides evidence against these outcomes being the drivers of such entry.

Overall, our interpretation of these results is that public pharmacies did not affect access to pharmaceutical drugs in a magnitude such that it improved adherence enough as to reduce avoidable hospitalizations. This lack of health effects is consistent with our results in section 4 showing that public pharmacies induced mostly substitutions from private pharmacies rather than expanding access to drugs to a broader population.

6.2 Municipal finance

Given that public pharmacies were created and managed by municipalities, it is important to understand whether these are economically sustainable or represent a financial burden. In principle, municipalities buy and sell at similar prices and their operation costs should be relatively small. However, mayors might not take full advantage of the public intermediary to meet the demand of their constituents. This section uses administrative data from the National System of Municipal Information to estimate the impact of public pharmacies on municipal finance.[30]

We observe annual spending and income in each year of the period 2013-2019. Both spending and income have subcategories that we aggregate into health and non-health categories. To facil-

[30]Municipalities spend resources in transportation, public education, public health, culture, and sports, among others (Law 18,695). Approximately 90 percent of their income comes from municipalities (property and vehicle tax receipts) and the rest of resources correspond to monetary transfers from the central government.

itate the comparison across municipalities, we follow previous literature and use the logarithm of spending (or income) per capita using population data in 2014 (Corvalán et al., 2018; Lara and Toro, 2019; Livert et al., 2019). We also define the deficit of a municipality as the ratio of spending and income. Econometrically, we estimate equation (5) using a panel data of municipalities observed annually (instead of monthly) and thus include year (instead of month) fixed effects. We again use municipality fixed effects and exploit the staggered entry of public pharmacies.

Table 8 presents estimates of equation (5). Columns 1-3 examine total spending, income, and deficit. Columns 4-6 and 7-9 the same outcomes but for the non-health and health categories respectively. These estimates deliver two key messages. First, public pharmacies are associated with an increase in health spending in column 7 that is almost entirely compensated by an increase in health income in column 8, leading to a 1.2 p.p. higher health deficit in column 9 (p-value 0.103). Second, municipal finance as a whole is unchanged: spending and income increase by a similar amount of 1.7-1.9 percent and as a consequence the municipal deficit in column 3 remains similar. Figure A.10 presents the corresponding event study estimates. These results suggests that public pharmacies crowd-out spending from non-health to cover the higher deficit in the health category.

To further understand the implications of our estimates, let us look at municipalities in 2014, before public pharmacies opened. At the time, the average annual income and spending in health were US\$102 and US\$100 per capita. Our point estimates in column 6 suggest that the average annual deficit in the health category increased by 1.2 percent, roughly US\$1.2 per capita (0.012×102) or US\$120,000 (1.2×100,000). These numbers suggest that the average monthly cost of public pharmacies is US\$10,000 (120,000 divided by 12). Crucially, Table 8 suggests that most of these resources are crowded out from other categories and as a consequence we observe that the average increase in municipal deficit in column 3 is only 0.2 percent with a 95 percent confidence interval of $[-0.010, 0.014]$. These estimates suggest that public pharmacies create a municipal loss of US\$10,300 monthly (0.2%×618×100,000/12) with a 95 percent confidence interval that spans a monthly loss of US\$72,000 and a monthly profit of US\$20,000.

Overall, public firms did not become a financial burden even though they sell at much lower prices than private pharmacies. In fact, public pharmacies are associated with equivalent increases in both spending and income, and have little to none effects on other (non-health) services provided by the municipality. Therefore, they are able to generate consumer savings by switching consumers away from the private option while remaining financially sustainable. This result can be explained by two conditions that characterize our setting and make the role of public firms potentially more relevant: local governments hold a cost advantage relative to private firms, and private firms hold substantial market power that translates into large markups over marginal costs (Fiscalía Nacional Económica, 2019).

7 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 emergence of a public competition 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 the local market, altogether consumer savings increased and mayors were politically rewarded for opening the pharmacy.

Although our study is grounded on a particular form of public/private competition, we believe it provides general lessons. The public option triggers general-equilibrium effects that can make some consumers worse off. In our context, these consumers are those with relatively high willingness to pay for service quality. Our analysis also highlights that public competition *per se* may not be able to solve some market failures and "discipline" the private market when strategic responses such as price increases are available for incumbent firms. Instead of calling against a public option, the results in this paper highlight the many complications that arise in their interaction with private firms, specially when the public option is of substantially worse quality.

The political rewards of public firms could be interpreted as showing that, as a whole, public firms increased citizen's welfare. However, we highlight 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 show suggestive evidence consistent with this interpretation as the majority of consumers in the market end up being worse off after the entry of the public option because of the higher prices in the private sector. These findings highlight the need to evaluate the market effect of policies instead of drawing conclusions of 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 public option was of the same or better quality than their private counterparts, then we would expect more people to switch and potentially higher benefits for the target population. However, 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 a change in the location of private stores or changes in store quality, among others. The findings in this paper call for more attention to potential general equilibrium effects to better understand if and when the public option can improve beneficiaries without damaging everyone else in the market.

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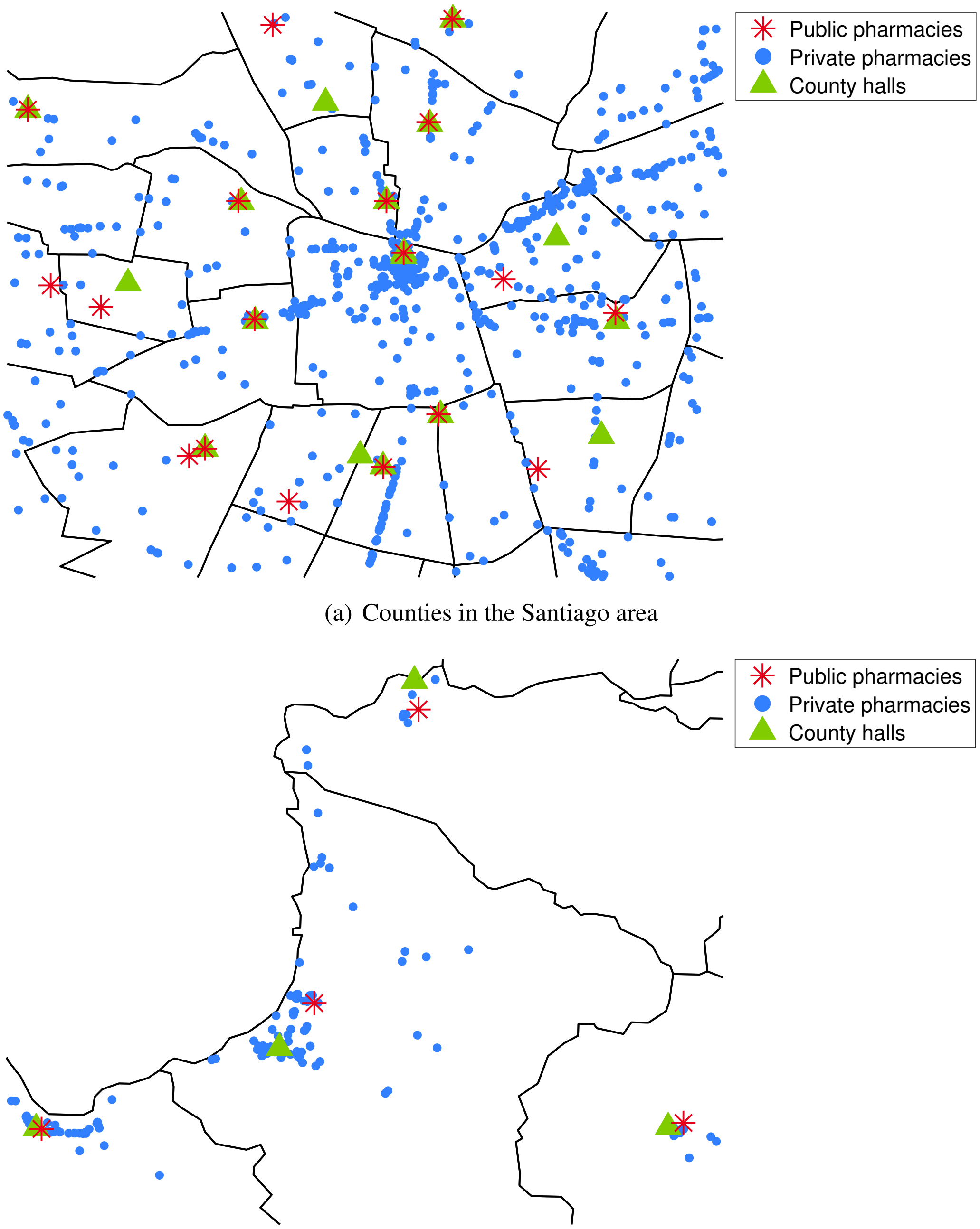
Figure 1: Locations of public pharmacies

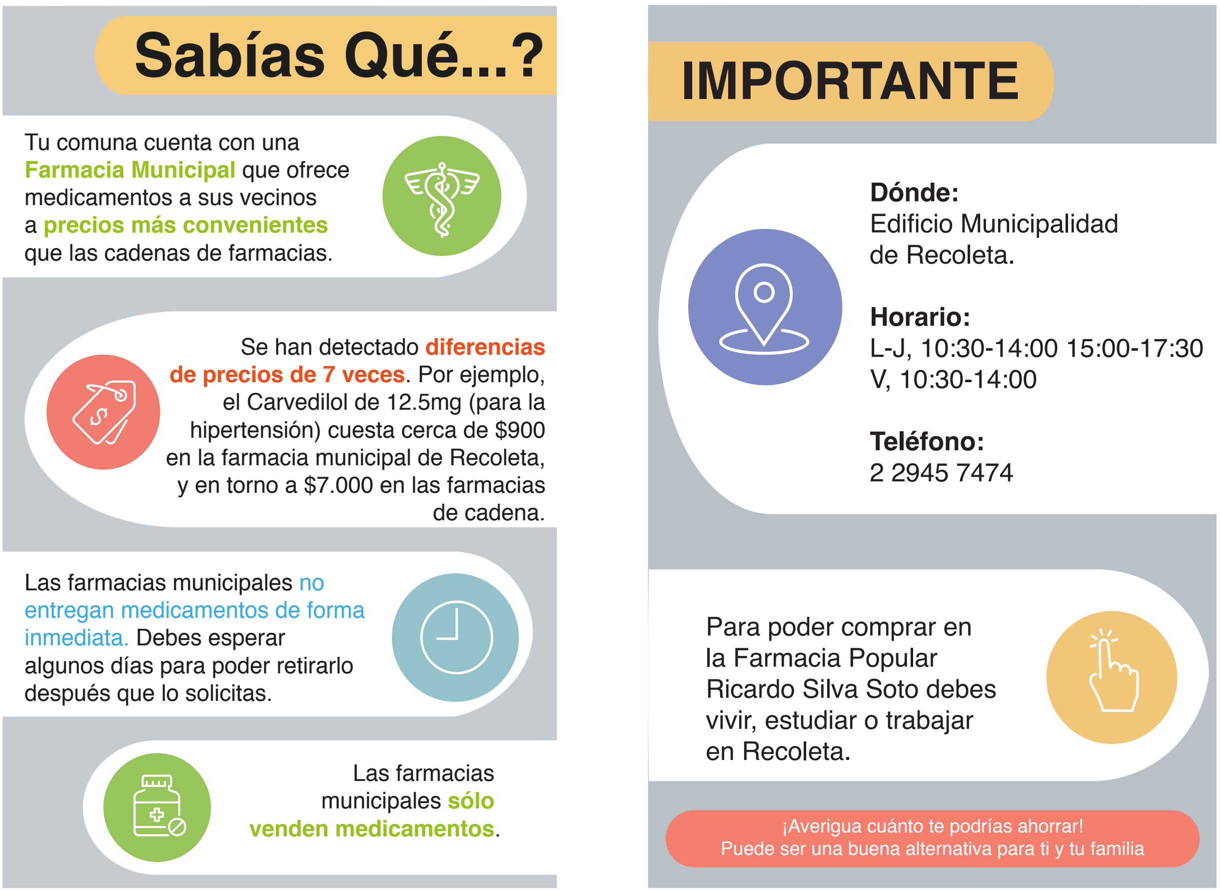


(a) Counties in the Santiago area

(b) Counties in the Valparaiso area

Notes: Own construction using geo-coded location of private pharmacies, public pharmacies, and county halls.

Figure 2: Informational treatment

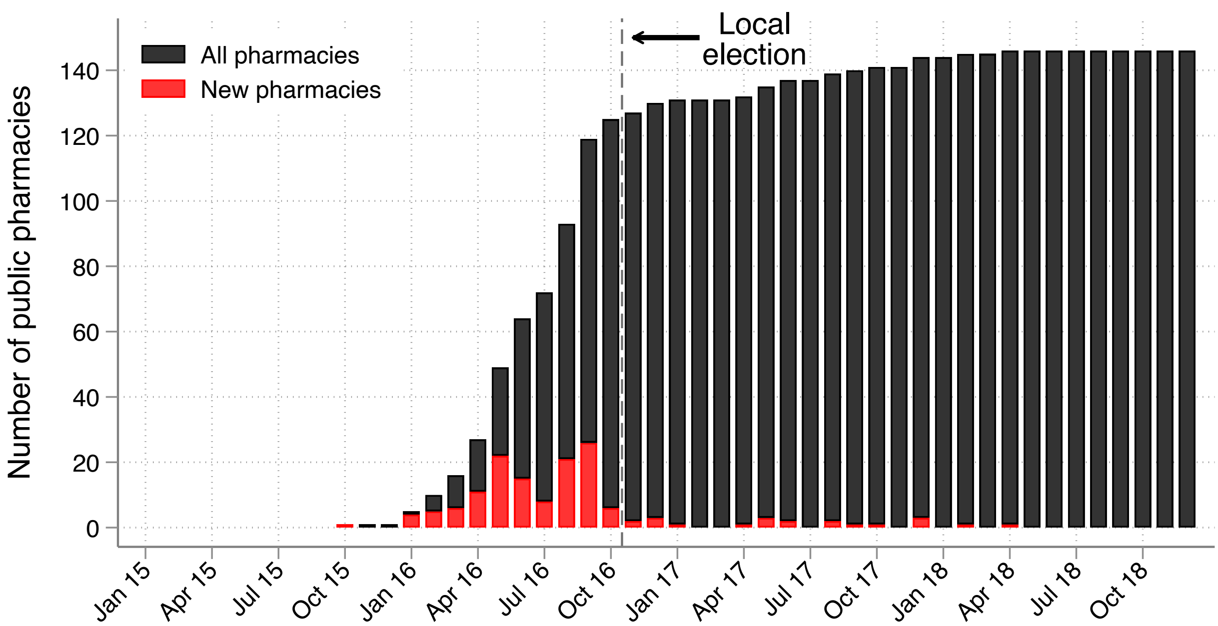


(a) Awareness and convenience

(b) Search details

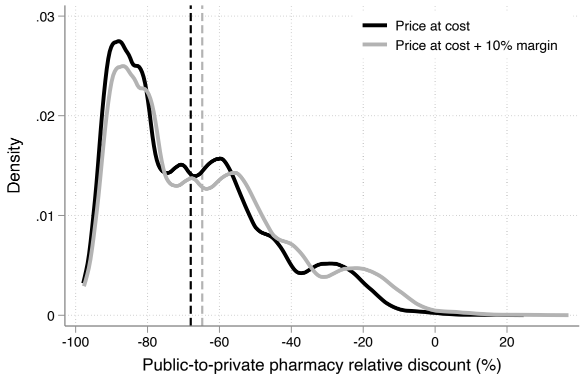
Notes: This figure displays the informational interventions delivered as part of the field experiment. Panel (a) displays the first part of the treatment, which aimed at increasing awareness about the public pharmacy. It introduced the public pharmacy and mentions that it offers lower prices than private 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 according the county of each participant.

Figure 3: Timing of entry of public pharmacies

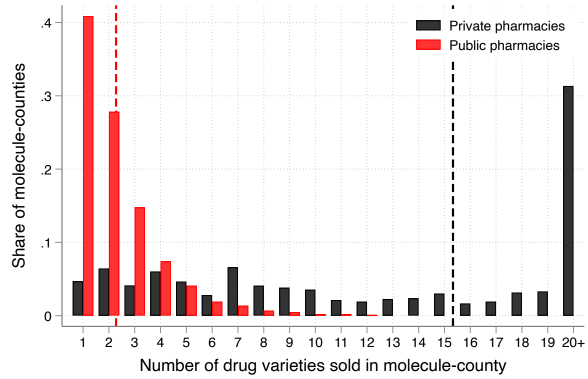


Notes: Own construction. The height of black bars indicate the number of active public pharmacies in a given month. The height of red bars indicate the number of new public pharmacies opened in a given month.

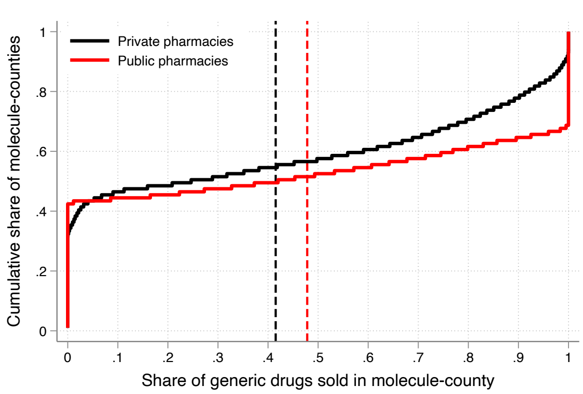
Figure 4: Relative prices between private and public pharmacies



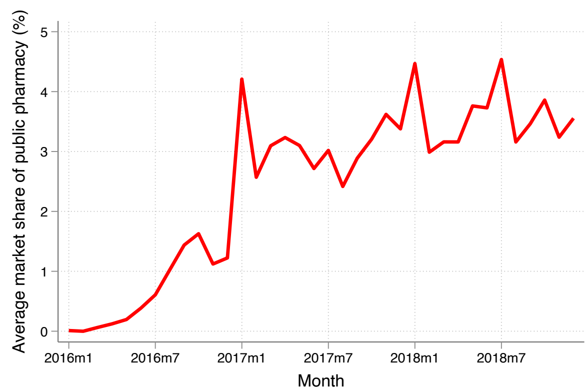
(a) Distribution of price discounts



(b) Number of drug varieties



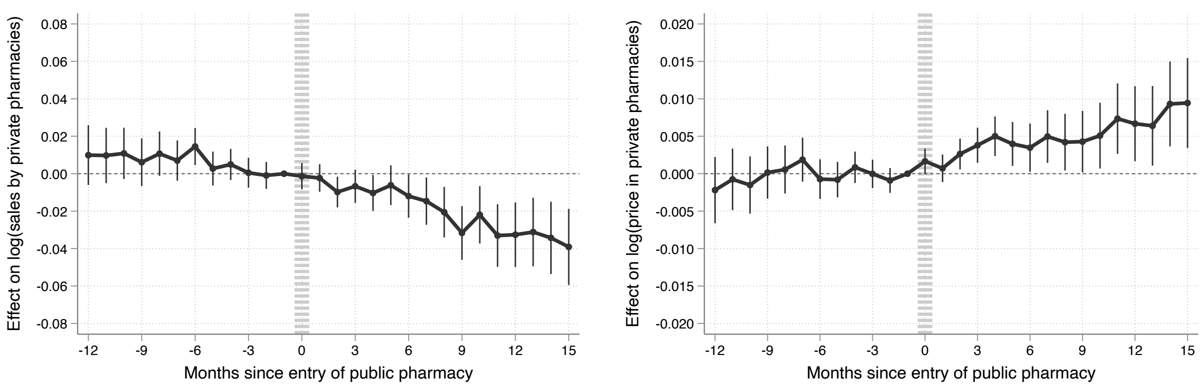
(c) Share of generic drugs



(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 IMS 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) 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 (c) displays the CDF of the share of drugs of a given molecule sold in a county that are generic, for public (red) and private (black) pharmacies during 2017–2018, whenever both private and public pharmacies sell at least one drug of the molecule. The dashed vertical lines indicate the mean generic shares for public (red) and private (black) pharmacies respectively. 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 event study specification in equation (2). 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. These regressions are estimated on a sample of 681,120 observations for sales 649,885 for prices. The number of observations changes from Panels (a) and (b) because we do not observe prices for months in which all drugs within a molecule display zero sales.

Table 1: 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's 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 IMS 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 2: Balance in covariates between treatment and control group

	(1)	(2)	(3)
Variable	Control	Treatment	*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 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(Subscribed)			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 subscription 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: 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)
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 6: Evaluation of mayors who opened pharmacies *before* the 2016 local election

	(1)	(2)	(3)
	Vote share incumbent coalition	Vote share incumbent mayor	Turnout
Distance from voters' home to pharmacy	-0.047***	-0.053***	0.021
× Opened *before* the election	(0.009)	(0.009)	(0.013)
Age of voters in booth	0.001*	0.001*	0.001
× Opened *before* the election	(0.001)	(0.001)	(0.001)
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.

Table 7: 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 (5). For each outcome, the first column uses the total 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 8: Municipal finance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log total			Log non-health			Log health		
	Spending	Income	Deficit	Spending	Income	Deficit	Spending	Income	Deficit
Public pharmacy	0.019	0.017	0.002	-0.012	-0.029	0.014	0.049***	0.036**	0.012
	(0.014)	(0.015)	(0.006)	(0.028)	(0.027)	(0.012)	(0.017)	(0.018)	(0.007)
Mean of dep. var. in levels in 2014	398	402	0.99	335	339	0.99	65	66	0.99
Observations	2,401	2,401	2,401	2,240	2,239	2,243	2,240	2,240	2,240
Municipalities	345	344	344	322	322	322	321	321	321
R-squared	0.963	0.961	0.325	0.896	0.909	0.236	0.965	0.958	0.228
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Annual data for all municipalities in the period 2013-2019. *Spending* and *Income* are measured in monetary units per capita. *Deficit* is defined as the ratio of spending over income. Standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

ONLINE APPENDIX

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

Juan Pablo Atal, José Ignacio Cuesta, Felipe González, and Cristóbal Otero.

List of Figures

List of Tables

A Additional results on market outcomes

A.1 Alternative specifications of event study

Alternative entry definition. In our main event study specification, we define the timing of entry as the time when the first county among the collection of counties in location l that adopts a public pharmacy. Yet there is no obvious way to define the entry event in our setting. In Figure A.4, display results for which we define the entry of a public pharmacy to the *largest* municipality in l—among counties for which there is an entry—as the event date for location l. Again, we find no differential pre-trends in sales and prices, and the results are quantitatively consistent with the findings using the timing of the first county to introduce a public pharmacy within the location.

Multiple events. A concern with our empirical specification is that the treatment does not differentiate between locations where multiple counties adopting a public pharmacy from counties with only one adopter. To tackle this issue, we estimate event studies where the unit is a molecule-by-location-by-event. Following Lafortune et al. (2018), 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 the main dataset and use the entry of public pharmacies in all counties within a location as event dates. We use location-by-event-by-molecule fixed effects instead of location-by-molecule effects. Figure A.5-a shows the distribution of events, and Figures A.5-b and A.5-c present the event study results for sales and prices respectively. Again, results are qualitatively and quantitatively similar to those from our main specification.

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:

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

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 4.2. Figure A.6 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:

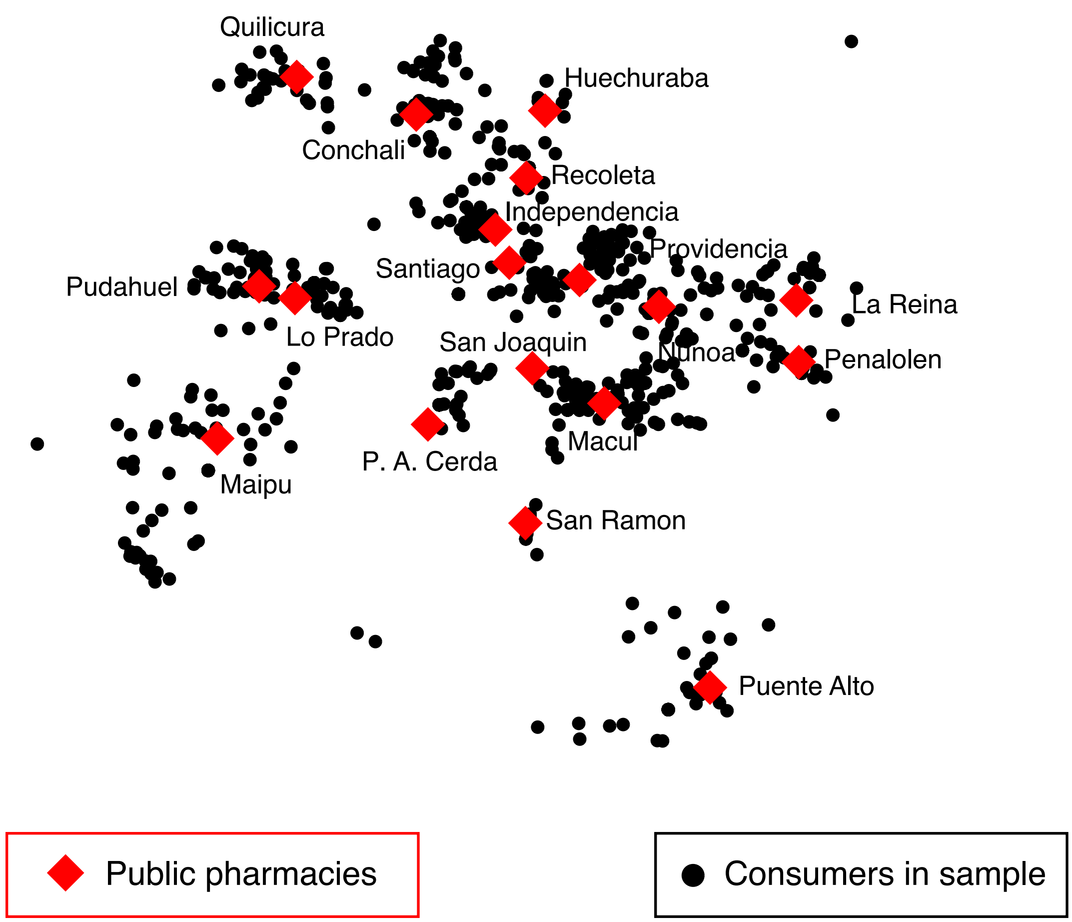
$$v = v_0 + (1 - v_0) \cdot e \cdot p \tag{7}$$

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: 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.2: Timeline of experiment events

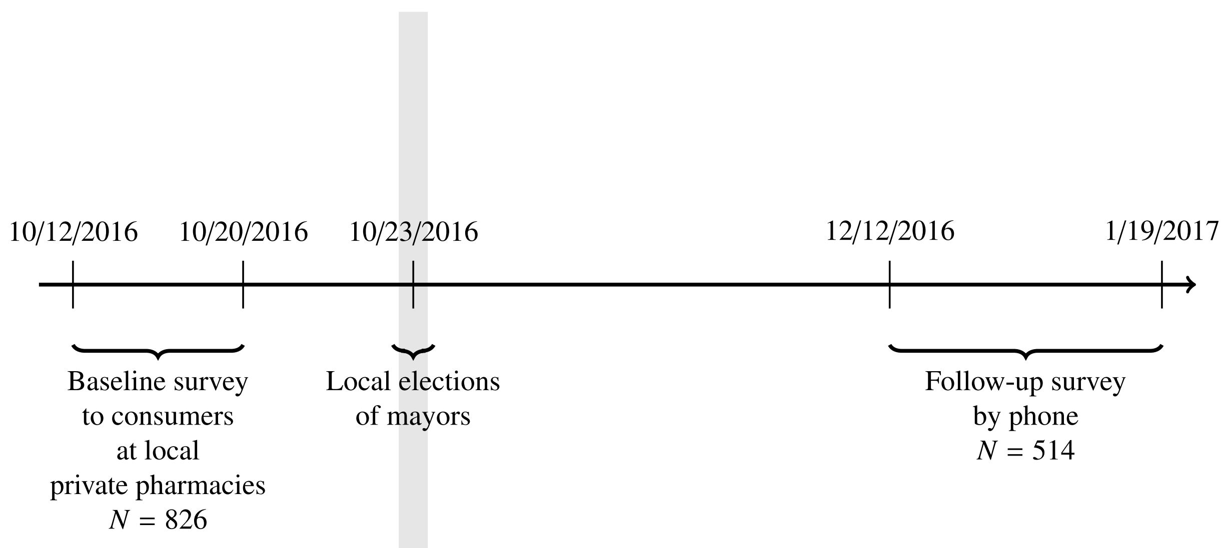
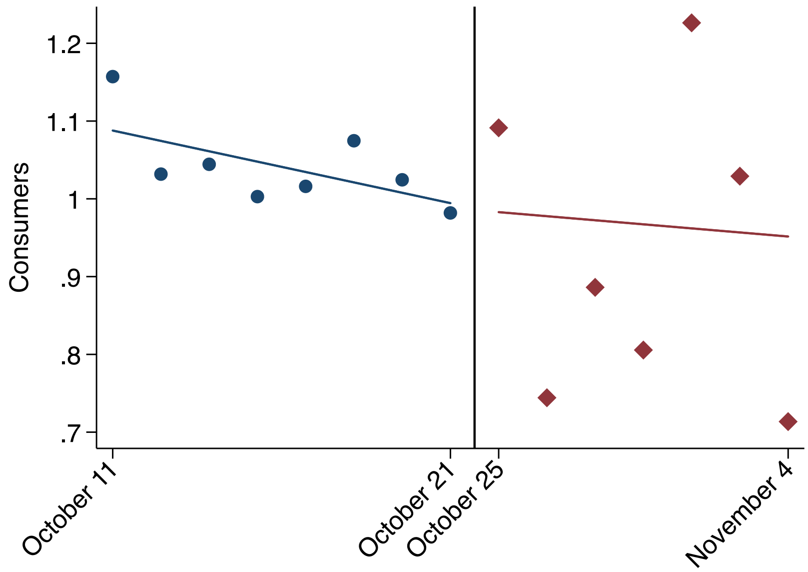
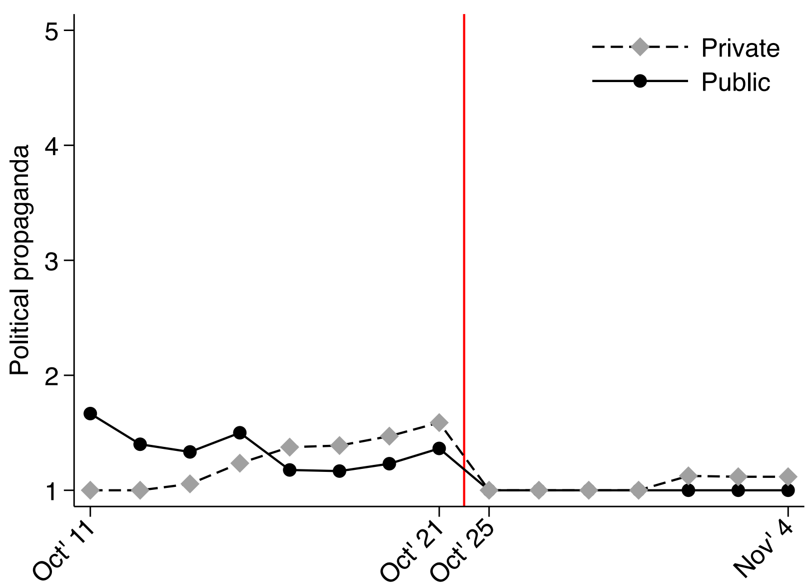


Figure A.3: Monitoring pharmacies around local elections



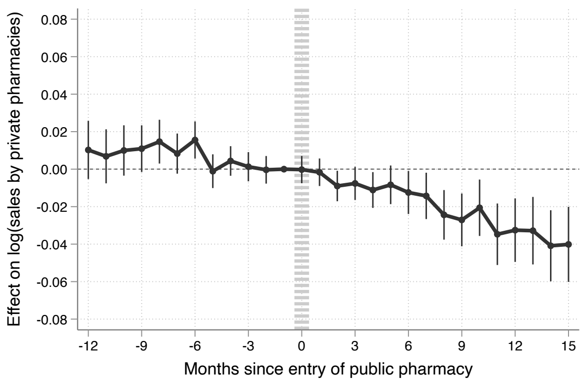
(a) Consumers per hour in public pharmacies



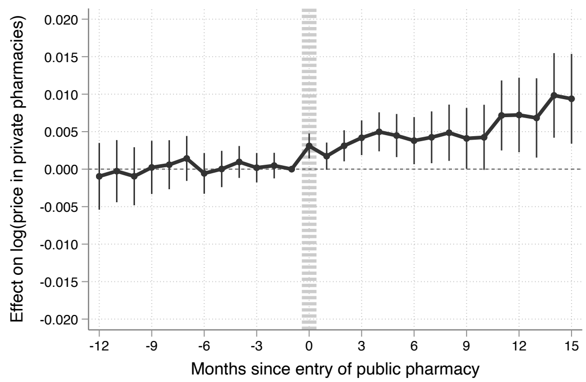
(b) Propaganda

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.4: Impact of public pharmacies: Entry is largest county



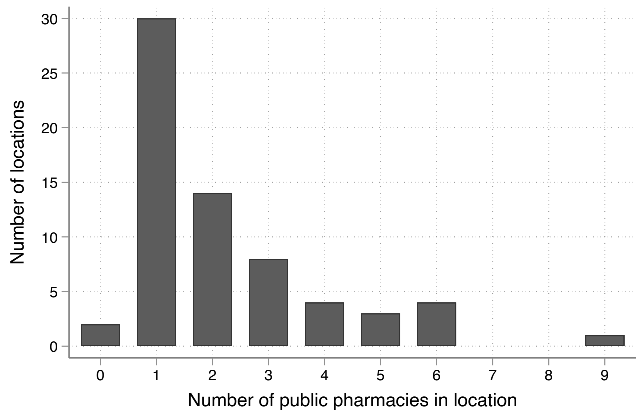
(a) Sales



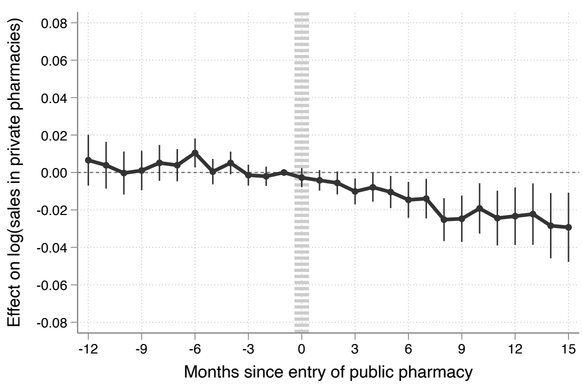
(b) Prices

Notes: *Notes*: This figure presents the coefficients of the event study specification in equation (2). 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. These regressions are estimated on a sample of 681,120 observations for sales 649,885 for prices. The number of observations changes from Panels (a) and (b) because we do not observe prices for months in which all drugs within a molecule display zero sales.

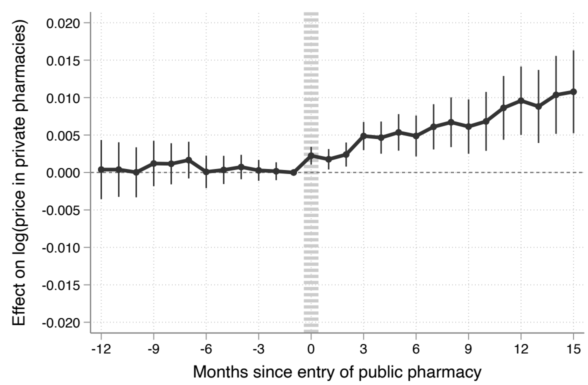
Figure A.5: Impact of public pharmacies: Multiple Events



(a) Number of events per location



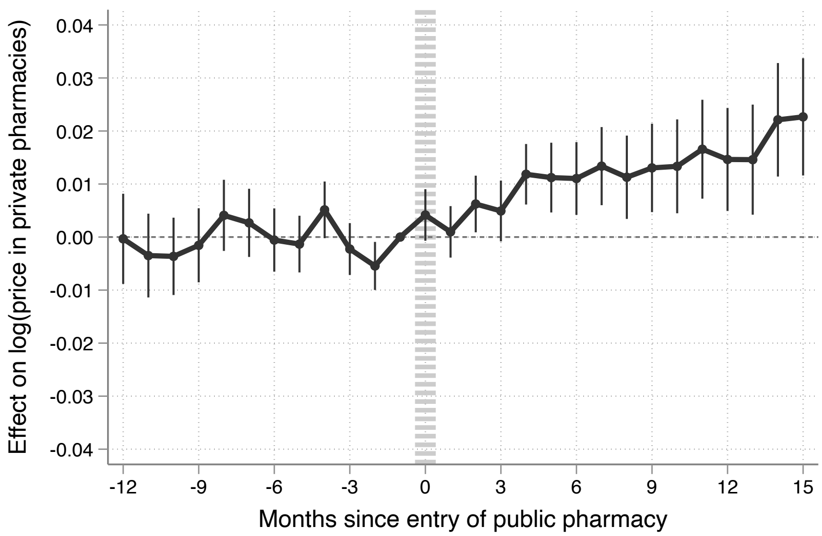
(b) Sales



(c) Prices

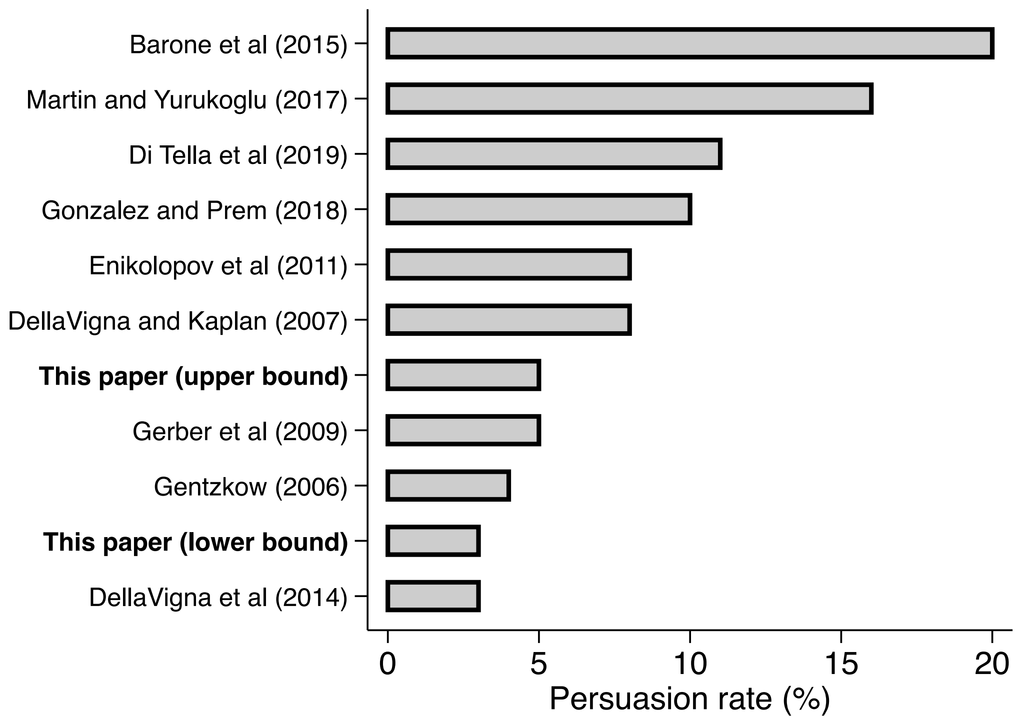
Notes: This figure presents the coefficients of the event study specification in equation (2), with multiple events. Locations with multiple events are stacked multiple times in the data. We allow a maximum number of 4 copies per location, although this choice does not change the magnitude of the results. 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. These regressions are estimated on a sample of 1,314,811 observations for sales and 1,374,060 observations for prices. The number of observations changes across Panels (b) and (c) because we do not observe prices for months in which all drugs within a molecule display zero sales.

Figure A.6: Impact of public pharmacies: Average paid prices



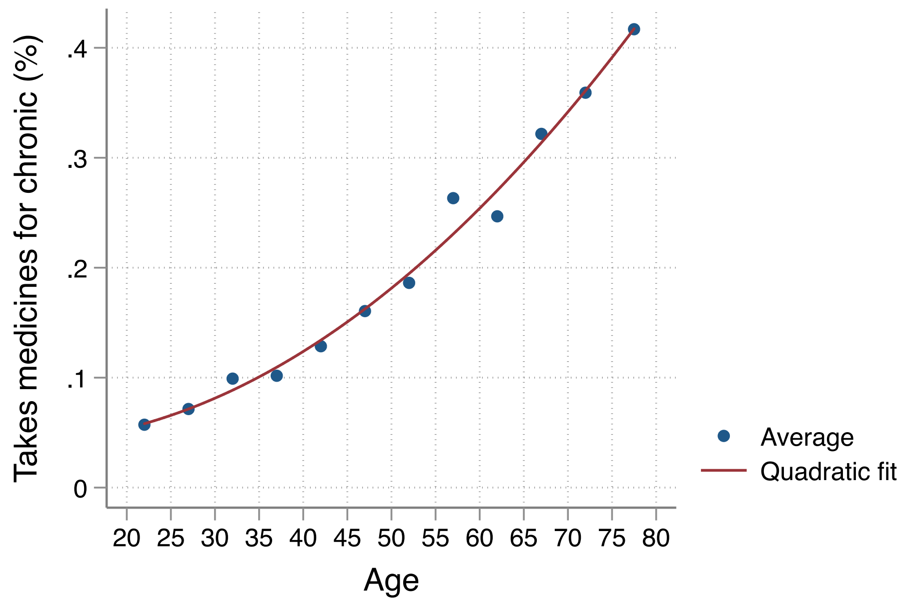
Notes: *Notes*: This figure presents the coefficients of the event study specification in equation (2). The timing of entry is defined as the first county to introduce a public pharmacy in the set of counties in location *l*. Dots indicate estimated coefficients, and vertical lines indicate the corresponding 95 percent condence intervals. These regression is estimated on a sample of 649,885 observations.

Figure A.7: Persuasion rates

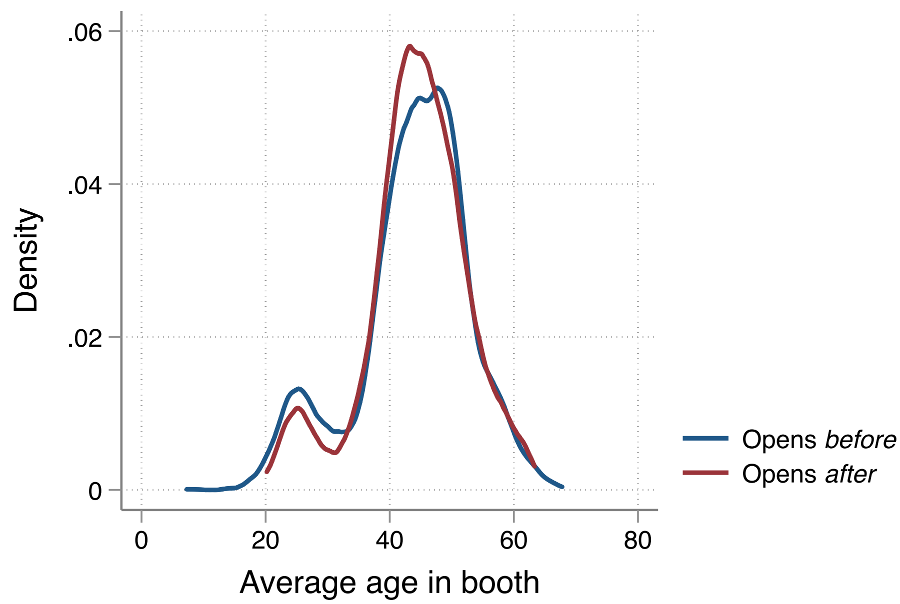


Notes: Own construction based on persuasion rates reported in DellaVigna and Gentzkow (2010).

Figure A.8: Age as proxy for chronic disease



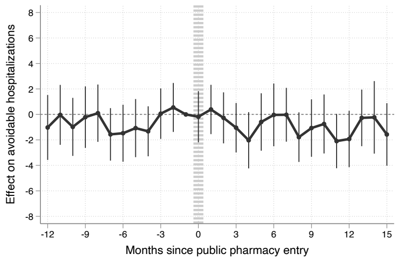
(a) Data from the National Health Survey



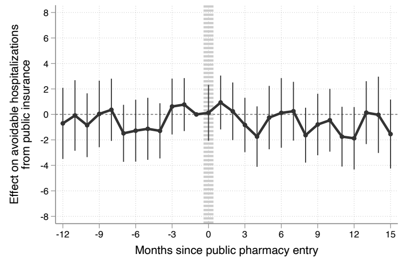
(b) Data from booth-level analysis

Notes: Own construction based on data from the National Health Survey in panel (a) and administrative data from the Electoral Service in panel (b).

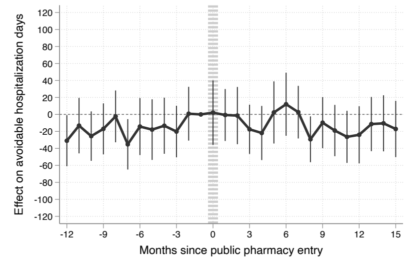
Figure A.9: Event study estimates for effects on avoidable hospitalizations



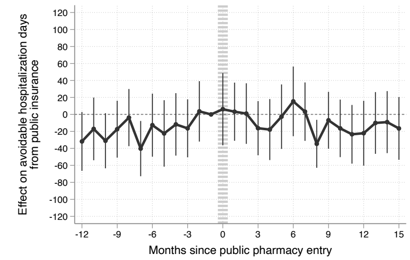
(a) Number of hospitalizations, all insurance



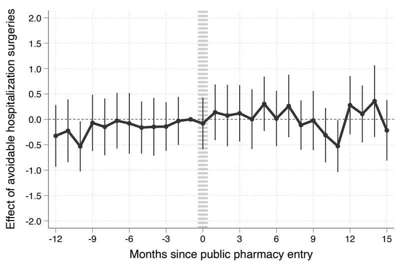
(b) Number of hospitalizations, public insurance



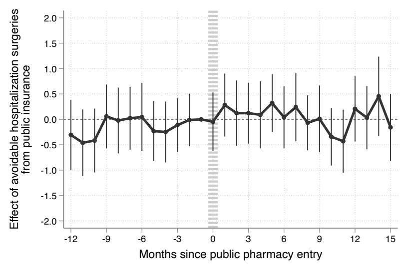
(c) Days of hospitalizations, all insurance



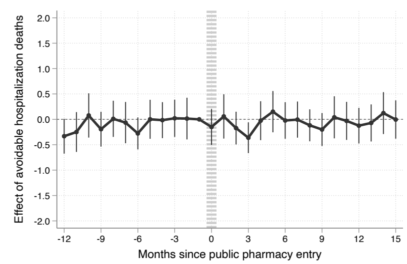
(d) Days of hospitalizations, public insurance



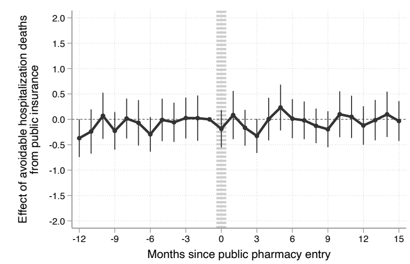
(e) Number of surgeries, all insurance



(f) Number of surgeries, public insurance



(g) Number of deaths, all insurance



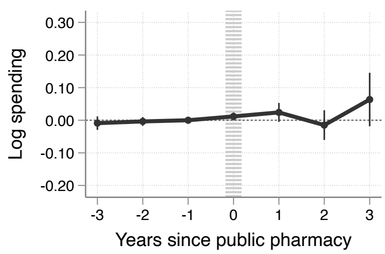
(h) Number of deaths, public insurance

Notes: Each plot displays results from an event study version of equation (5) given by:

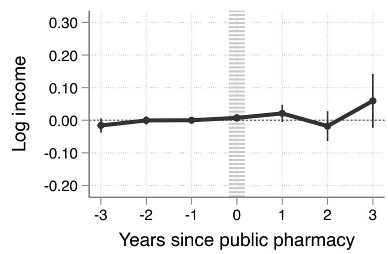
$$y_{ct} = \sum_{k=-12}^{15} \beta_k D_{ct}^k + \theta_c + \lambda_t + \varepsilon_{ct}$$

where the outcomes are the same measures of avoidable hospitalization events as in Table 7 and treatment dummies are defined as in equation (2). Each dot is coefficient and vertical lines indicate the 95 percent condence intervals.

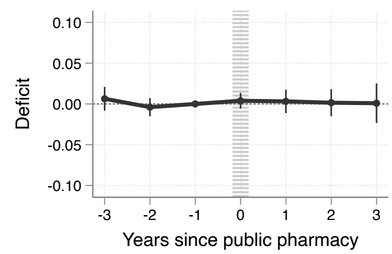
Figure A.10: Event study estimates for effects on municipal finance



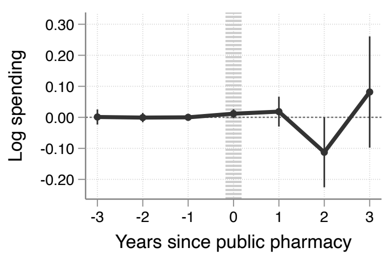
(a) Total spending



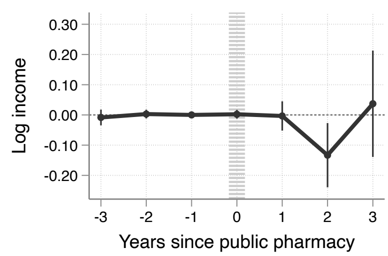
(b) Total income



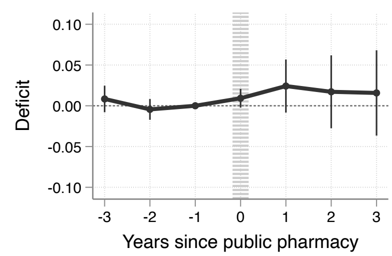
(c) Total deficit



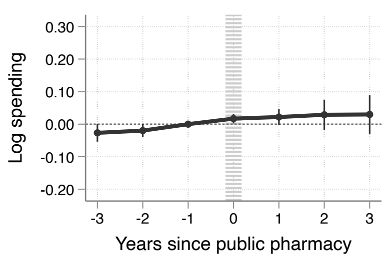
(d) Non-health spending



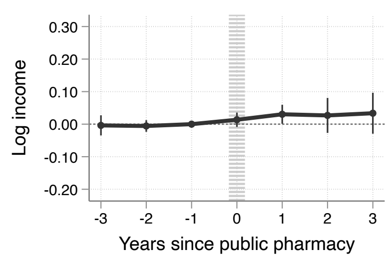
(e) Non-health income



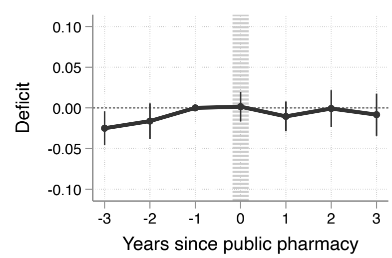
(f) Non-health deficit



(g) Health spending



(h) Health income



(i) Health deficit

Notes: Spending and income are measured in monetary units per capita. Each plot displays results from an event study version of equation (5) given by:

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

where the outcomes are the same measures of municipal finance as in Table 8 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)
	Cell size is (in meters):				
	1,000	800	600	400	200
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)
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. 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.

Table A.6: Evaluation of mayors, robustness of booth-level results

	(1)	(2)	(3)
	Vote share incumbent coalition	Vote share incumbent mayor	Turnout
Log distance from voters' home to pharmacy	-0.078***	-0.102***	0.038
× Opened *before* the election	(0.024)	(0.021)	(0.026)
Age of voters in booth	0.001*	0.001*	0.001
× Opened *before* the election	(0.001)	(0.001)	(0.001)
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.