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

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Abstract

We study the effects of competition by state-owned firms, leveraging the decentralized entry of public pharmacies to local markets in Chile. Public pharmacies sell the same drugs at a third of private pharmacy prices, because of stronger upstream bargaining and downstream market power in the private sector, but are of lower quality. Public pharmacies induced market segmentation and price increases in the private sector, benefiting the switchers to the public option but harming the stayers. The countrywide entry of public pharmacies would reduce yearly consumer drug expenditure by 1.6 percent, which outweighs the costs of the policy by 52 percent.

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1 Introduction

State-owned firms compete with the private sector in education, healthcare, insurance, and basic services, among others. Supporters of the public option argue that it helps discipline markets that fail to provide enough incentives for private competition, either because of information asymmetries, market power, collusive behavior, or other market failures (Atkinson and Stiglitz, 1980). In contrast, critics argue that public firms might be inefficient, provide low quality, or be captured by political interests (Shleifer and Vishny, 1994; Shleifer, 1998). Estimating the equilibrium effects of the public option 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 its distributional consequences.

In this paper, we study the decentralized and large-scale entry of public retail pharmacies in Chile, where pharmacies managed by local governments entered 147 of the 345 counties between 2015 and 2018. Public pharmacies emerged as non-profit competition to a fully deregulated and highly concentrated private retail market characterized by high prices.[1] Public pharmacies sell drugs at prices that are 34 percent of those charged at their private counterparts. These low prices are possible both because private pharmacies hold substantial market power and because public pharmacies have a cost advantage. On the other hand, public pharmacies are of lower quality than their private counterparts: they require three times larger travel distances, carry less product variety, have more restrictive operating hours and longer waiting times.

To estimate the impacts of public pharmacies, we combine a field experiment to study individual responses to the entry of public pharmacies, with quasi-experimental approaches to study aggregate outcomes and account for potential equilibrium effects. The field experiment consisted of an informational intervention to consumers, which we randomly provided during the weeks preceding the 2016 local election in counties with public pharmacies. The treatment covered the existence, location, low prices and low convenience of public pharmacies. We surveyed consumers before the intervention and two months after it, collecting data about drug shopping behavior and political participation. The quasi-experiment exploits the staggered entry of public pharmacies across counties. To support this design, we show that the timing of entry was unrelated to baseline differences or pre-trends in local market attributes. Moreover, anecdotal evidence suggests that the timing of entry of public pharmacies depended partly on unexpected delays in the bureaucratic procedure for obtaining sanitary permits.

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

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

At the aggregate level, the entry of public pharmacies impacted private sector market outcomes. We exploit the staggered entry of public pharmacies and drug-level data to estimate their impact on private pharmacy prices and sales. A year and a half after opening, the average public pharmacy had shifted 4 percent of sales away from private pharmacies. The decrease in sales was concentrated among drugs targeted towards chronic conditions, which is consistent with our experimental evidence. We also find a *positive* and growing effect of public pharmacies on private sector prices: by the end of our sample period, the entry of public pharmacies had induced private pharmacies to increase their prices by 1.1 percent. We interpret this positive price effect as evidence that this low-price and low-quality public option generated market segmentation. In particular, private pharmacies responded to a shift of relatively price-sensitive consumers towards public pharmacies—and thus a less elastic residual demand—by increasing prices. This result is consistent with theoretical research on the potential for price-increasing competition (Chen and Riordan, 2008). A simple model of competition with differentiated firms rationalizes the lack of a stronger demand shift to public pharmacies despite their low relative prices, as coming from their low relative quality. These results show that public pharmacies generated winners and losers as a consequence of its equilibrium effects.

The reduction in consumer drug expenditure generated by public pharmacies is substantially larger than their costs. We develop a simple accounting framework to implement this comparison. First, we estimate the cost of public pharmacies using data on municipal finances. We find that public pharmacies increased public spending on health services by more than the revenue derived from them. Second, we quantify the benefits that public pharmacies provide to consumers. Combining our estimates of economic effects with summary statistics on drug expenditures and prices, we find that introducing public pharmacies in every county would reduce yearly drug expenditure by 1.6 percent or US$60 million, which is 52 percent higher than the cost of the policy.[2] Equilib-

[2]In addition to its economic effects, increased access to drugs could improve prescription adherence and thus health outcomes. Using data on avoidable hospitalizations and deaths, we find no evidence of such effects. This null

rium price responses by private pharmacies are quantitatively relevant, and omitting them would lead to overestimating the reduction in expenditure by 68 percent.

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

Overall, we show that public pharmacies created winners and losers: consumers who switched to public pharmacies benefited from lower prices and those who did not lost from higher prices. The public option did not become a financial burden because of their higher bargaining power in the input market and because private pharmacies hold substantial market power in the retail market. Our paper highlights that state-owned firms could be particularly effective in other contexts where these two conditions are also met. By doing so, we inform the long-standing question of state versus private ownership of firms, and the desirability of introducing a public option into otherwise private markets. Experiences of a public option exist in a variety of settings including trash collection, mail delivery, housing finance, and internet service providers in the U.S., and historically in retail gasoline stations in Canada (Petro Canada). Recent calls for the introduction of public option in the U.S. include non-commercial banking, mortgages and most notably healthcare.[3]

Most previous empirical work has studied public competition in the context of large programs in education (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., 2021). Recent work has focused on the role of state-owned firms in local markets, either directly managed by the central government as in the case of milk stores in Mexico (Jiménez-Hernández and Seira, 2020), or outsourced to the private sector in the Dominican Republic and Indonesia (Busso and Galiani,

result justifies our focus on reduced drug expenditure as a measure of benefits from public pharmacies.

[3]See e.g., "Why America needs a public option for mortgages" by Jeff Spross (The Week, 2017), or "There Should Be a Public Option for Everything" by Ganesh Sitaraman and Anne L. Alstott (The New York Times, 2019).

2019; Banerjee et al., 2019). Relatedly, Handbury and Moshary (2021) study the price responses of grocery stores following the expansion of the national school program in the U.S. This work mostly finds that prices decrease upon increasing public competition. Our paper contributes to this literature by studying the effects of entry of locally managed public firms into local pharmaceutical markets, and by showing that public firms can potentially induce market segmentation and lead to an increase in prices by private firms.

This paper also contributes to a literature studying how store entry affects local market outcomes (Basker, 2007; Hausman, 2007; Jia, 2008; Matsa, 2011; Atkin et al., 2018; Arcidiacono et al., 2020; Bergquist and Dinerstein, 2020). The extent to which entry can generate segmentation in differentiated product oligopoly markets has been studied theoretically by Chen and Riordan (2008). Empirically, Frank and Salkever (1997) and Ward et al. (2002) provide evidence for price increases by incumbent products upon entry of generic drugs and private-label consumer packaged goods. We contribute to this literature by studying the consequences of entry by low price and low quality firms and providing evidence of market segmentation.

Our analysis of political support for incumbent mayors who opened public pharmacies is related to a large literature that studies if and how information about politicians and policies can shape political preferences. Previous research has studied the impact of information about the candidates in an election, incumbent policies, and the prevalence of corruption (Ferraz and Finan, 2008; Gerber et al., 2011; Chong et al., 2015; Kendall et al., 2015; Dias and Ferraz, 2019). Our experimental analysis differs from previous work by providing information about a specific policy directly to the people most likely to be affected by it and only a few weeks before the election.[4] More generally, we contribute to the existing literature by providing novel evidence of political returns to the introduction of state-owned firms in local markets.

Finally, this paper contributes to the literature analyzing policies that aim at increasing access to pharmaceuticals. Although access to affordable drugs is a first-order policy concern in low- and middle-income countries, which policies should regulators implement to achieve this goal is a debated issue (UN, 2010; Pinto et al., 2018). Recent work studies the effects of increased competition in the retail market. Moura and Barros (2020) studies the price effects of competition in the market for OTC drugs, while Bennett and Yin (2019) studies the price and quality effects of the entry of pharmacy chains in a market dominated by low-quality firms. Other research focuses on the effects of policies to lower drug prices, including price regulation (Dubois and Lasio, 2018; Dubois et al.,

[4]The focus on health relates our paper to recent work on the effects of the Medicaid Expansion on voter registration and turnout (Haselswerdt, 2017; Clinton and Sances, 2018; Baicker and Finkelstein, 2019).

2019a; Mohapatra and Chatterjee, 2020; Maini and Pammolli, 2021), quality regulation (Atal et al., 2019) and public procurement (Dubois et al., 2019b; Brugués, 2020). We provide novel evidence of how public competition in the retail market affects equilibrium market outcomes.

2 The public option in retail pharmaceutical markets

Before the introduction of public pharmacies, consumers could obtain pharmaceutical drugs by buying from private pharmacies or from public health care providers. According the 2016-2017 National Health Survey (*Encuesta Nacional de Salud*, ENS), 40 percent of pharmaceuticals were purchased in the private retail sector, where there is limited insurance coverage. In fact, pharmaceuticals are the most important item of out-of-pocket health expenditures in the country (OECD, 2015; Benítez et al., 2018).[5] The private sector is highly deregulated, as there are no market structure regulations or price controls. The three largest chains account for around 80 percent of the market share (FNE, 2019), and stores are geographically clustered in relatively rich areas (MINECON, 2013). Margins for manufacturers and retailers were high during our period of study, at almost 50 percent and 40 percent respectively (FNE, 2019).

The rise of public pharmacies was preceded by a collusion scandal in the pharmaceutical industry in 2008 that involved the three largest pharmacy chains in the country (Alé-Chilet, 2018). In a high profile antitrust case, the pharmacy chains were found guilty. A left-wing mayor of a large county listened to public demands and opened the first public pharmacy in October 2015. Soon after, the popularity of the mayor boomed and dozens of other mayors from all political parties decided to open public pharmacies in the following months. By the end of 2018, 147 out of the 345 counties in the country were operating a public pharmacy. Figure 1 plots the number of counties with a public pharmacy over time and Figure A.1 display photos of a private and public pharmacy.

Public pharmacies offer lower prices because they operate as non-profit firms by law and have a cost advantage. The latter comes from their use of the public intermediary that aggregates demand from public providers to negotiate lower prices with laboratories (FNE, 2019). The beneficiaries of public pharmacies are determined by a combination of eligibility requirements, health conditions and location. Most public pharmacies require consumers to reside in the county and offer prescription drugs with a focus on drugs targeting chronic conditions. Hence, individuals with chronic conditions are more likely to benefit. Finally, public pharmacies enter the market with a single

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

location per county, whereas there are multiple private pharmacies in each market, which implies that for most consumers travel costs to public pharmacies are higher than to private pharmacies.

The increasing popularity of public pharmacies has been surrounded by economic and political controversies. On the economic side, there are two main criticisms. First, that public pharmacies may be financially unsustainable and could become a burden for local governments. Second, that public pharmacies could be a form of unfair competition particularly towards non-chain private pharmacies, which accounted for 10 percent of the market, had limited buying power, and were not involved in the collusion scandal. These criticisms motivate part of our analysis, particularly the impact of public pharmacies on private sector outcomes and municipal finances.

3 Data

We collected the opening dates and locations of public pharmacies. Openings span the period between October, 2015 and April, 2018. Figure 1 shows the number of openings per month and the evolution of the total number of public pharmacies operating over time. Their opening before the local election in October 23, 2016 – in which most incumbent mayors were running for reelection – seemed far from a coincidence for many. The abrupt increase in openings during the months before the election is hard to explain without resorting to a political argument.

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

To measure outcomes for private pharmacies, we use data from IQVIA, a company that collects pharmaceutical market information worldwide. These data contain monthly local drug prices and sales for 2014-2018 collected from two sources. The four largest pharmacy chains, which account for more than 90 percent of market share, report retail prices and sales directly to IQVIA. Data for other pharmacies are collected from wholesalers.[6] IQVIA aggregates the data at the level of 66

[6]We adjust these prices for inflation using the health CPI from the National Institute of Statistics and compute prices per gram of the active ingredient to normalize them across presentations.

local markets, which cover most of the country.[7] We restrict our attention to prescription drugs, which account for 93 percent of the drugs among the molecules we include in the analysis.

4 Research design

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

4.1 The field experiment

We designed a field experiment to study whether the availability of public pharmacies affected consumer shopping behavior. To induce variation in awareness about the public pharmacy in their local market, we implemented an informational intervention. The decision to provide information was based on a survey we conducted before the experiment, which revealed that consumers were only partially informed along two dimensions. First, some households were unaware of the existence of a public pharmacy in their county. Second, even when households knew about the pharmacy, they were not perfectly informed about the lower prices and other attributes. The existence of imperfect information provides us with a unique opportunity to randomly expose consumers to public pharmacies using our experiment, and thus to measure individual responses to them.

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

In terms of recruitment, enumerators approached consumers leaving a private pharmacy in each county and assessed their eligibility. Eligible participants were those who (i) lived and were

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

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

Two months after the baseline survey, we conducted a follow-up survey to measure the same variables as in baseline. Additionally, we collected information about their relationship with the public pharmacy in their county. We implemented this survey by phone, and were able to complete the survey for 514 participants, almost two thirds of the sample.[8,9]

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

4.2 The entry of public pharmacies

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

We start by comparing counties with and without public pharmacies. Columns 1-3 in Table 2

[8]Table A.3-A shows that attrition was higher among younger participants, males, with higher support for the incumbent, less turnout in the last election, and less knowledge of the public pharmacy. While this changes the sample composition and decreases the statistical power of the experiment, it does not necessarily threatens its internal validity. Table A.3-B shows that all variables are balanced across groups among non-attriters.

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

show these results. The upper panels show that public pharmacies opened in dense high-income counties with more penetration of private health insurance, slightly better self-reported health, and with a private pharmaceutical market with more pharmacies, more sales and higher prices. In contrast, the lower panel shows few differences in political variables as measured by the previous local election of 2012.[10] If anything, counties with a public pharmacy had more candidates, and were more likely to have a winner from the left-wing. In sum, counties with and without public pharmacies differ significantly in terms of their pharmaceutical market and socioeconomic characteristics but were relatively more similar in their political characteristics.

To examine the timing of entry systematically, we ranked all public pharmacies by their entry date and estimated an ordered logit model of this ranking on all variables in Table 2. Column 4 in this table presents results. Pharmacies opening earlier entered counties with more population and are more likely to be run by left-wing mayors, but the timing of entry is otherwise uncorrelated with the characteristics of the pharmaceutical market, with socioeconomic attributes, and with electoral competition in the previous election. Instead, anecdotal evidence suggests that unexpected delays in sanitary permits explain why some pharmacies opened after the election. We rely on these results to exploit the timing of entry as exogenous variation.

Finally, we document that mayors opened public pharmacies nearby existing private pharmacies, providing a unique opportunity to study the impact of the public option in an existing market. To describe their location choices, we geocoded all private pharmacies in the country and assigned them to geographic cells of 600×600 meters. We then estimated cross-sectional cell-level regressions using data from counties with a public pharmacy. The dependent variable is an indicator for a cell having a public pharmacy and the explanatory variables include the number of private pharmacies, the number of schools as a proxy of population, and county-level fixed effects. Table A.1 displays the results. The estimates reveal that public pharmacies opened in populated areas where private pharmacies were already operating. The maps in Figure 3 provide visual examples of the entry decision in six counties.

[10] In Chile, all mayors are elected simultaneously by a simple majority rule in elections held every four years and without term limits. To measure local political outcomes we use county-level information about candidates, parties, coalitions, and votes by candidate in the 2012 and 2016 local elections from the Electoral Service. The 2012 election allows us to characterize the political equilibrium before the opening of public pharmacies.

5 Economic effects of public pharmacies

5.1 Descriptive evidence on prices and quality

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

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

Consumers trade-off lower prices with lower quality of public pharmacies. The fact that public pharmacies enter with a single store in each county implies that most consumers have multiple private pharmacies closer to their homes. Using our data on voter home addresses and public and private pharmacy locations, we calculate distances between households and every pharmacy in the county. The average (median) individual has 20 (12) private pharmacies located closer than the public pharmacy in their county. Figure 4-b shows that the distributions of distance to the closest private pharmacy and the public pharmacy differ markedly. In fact, the average distance to the closest private pharmacy is 0.6 kilometers, less than a third than that to the public pharmacy. These facts imply that shopping at public pharmacies involve higher travel costs than shopping at private pharmacies. Moreover, public pharmacies offer less product variety. Figure 4-c shows that the average number of products per molecule-county is 2.2, and that 70 percent of molecule-counties offer 3 varieties or less, while the average number of varieties in private pharmacies is 15.2.[11] To the extent that consumers value product variety, these patterns imply that public pharmacies are less convenient than private pharmacies. Longer waiting times and limited opening hours already mentioned in section 2 further exacerbate the relatively low quality of public pharmacies.

The relevance of public pharmacies has grown over time, reflecting that at least some con-

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

sumers value lower drug prices relative to lower convenience enough as to switch to public pharmacies. Figure 4-d shows that their average market share across molecules and counties reached around 4 percent by the end of 2018. Of course, it is unclear whether sales by public pharmacies have decreased sales by private pharmacies or rather expanded market size. To inform this margin, we estimate the effects of public pharmacies on private pharmacy sales in section 5.3.

5.2 Experimental evidence on shopping behavior

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

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

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

Information about public pharmacies made consumers more aware about their availability and attributes. Table 3-A displays these results. Columns 1 and 2 show that information increased awareness about the availability of the public pharmacy by 7 percentage points, from a baseline level of 77 percent. Moreover, columns 4 and 5 show that information shifted consumer perceptions about drug prices at public pharmacies, which is their most salient attribute. In particular, perceived public pharmacy prices decreased by 9 percent as a result of the intervention. We also find that perceived waiting time for receiving drugs at the public pharmacy increased, which is their main disadvantage relative to private pharmacies. In particular, perceived waiting time increased by 20 percent.[12] 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.

[12]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.

Consumers also seem to have reacted to the intervention in terms of shopping behavior. Table 3-B displays results from linear probability models for enrollment on the public pharmacy, the decision to purchase, and the plan to use the pharmacy in the future. Although the estimates are imprecise, they are positive and economically meaningful. The point estimate in column 2 indicates a 2 percentage points increase in enrollment on public pharmacies by treated households, almost a 30 percent increase relative to the mean of the control group. The results in column 5 imply a 2.3 percentage points increase in purchases in public pharmacies by treated households, more than an 80 percent increase relative to a baseline share of 2.8 percent in the control group. Finally, column 8 shows that our intervention increased the extent to which households plan to use the public pharmacy by 5 percentage points, as much as 10 percent relative to the baseline level for the control group.

Households with members that suffer chronic conditions react more strongly to the treatment. Columns 3, 6, and 9 study heterogeneity along this margin. All effects are larger for households with chronic conditions, although the differences are not statistically significant. Moreover, the treatment effects on effective and planned purchases are marginally statistically significant for consumers with chronic conditions. Consumers with chronic conditions are a group more likely to periodically shop for drugs and, thus, the group for which short term effects are more likely to be detectable. Moreover, in many cases public pharmacies prioritize the provision of drugs treating chronic conditions, thus the information in our intervention may be less relevant for consumers without any household member with a chronic condition. Treatment effects on consumers without a household member with a chronic condition are indeed close to zero across outcomes.[13]

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

5.3 Equilibrium effects on prices and sales by private pharmacies

Public pharmacies may induce consumers to substitute away from private pharmacies. Moreover, the competitive pressure from public pharmacies may induce private pharmacies to adjust prices.

[13] 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.

In this section, we estimate the effects of the entry of public pharmacies on prices and sales by private pharmacies.

Theoretically, the effects of entry on incumbent firms' prices are ambiguous. Chen and Riordan (2008) study the conditions under which entry leads to increases and decreases in prices. Their analysis shows that these effects depend on the magnitudes of two effects of entry on the incumbent's pricing incentives. First, entry has a *market share effect*, which depends on the extent to which the incumbent loses demand upon entry due to substitution. The more demand the entrant takes away from the incumbent, the stronger the incentives for the incumbent to decrease prices in response to entry. Second, entry has a *price sensitivity effect*, which depends on how the slope of the incumbent's residual demand curve changes after entry. The steeper the demand curve is after entry relative to before entry, the lower the extent of substitution away from the incumbent upon entry, and therefore the stronger its incentive to increase prices upon entry. Overall, the incumbent's price will increase whenever the price sensitivity effect dominates the market share effect, and vice versa. Which effect dominates depends on the distribution of consumer preferences and on the attributes of the firms. To further develop intuition for the conditions under which private pharmacy prices may decrease or increase upon the entry of public pharmacies, we develop a model based on Chen and Riordan (2008) in Appendix A. We then implement illustrative simulations that we employ to discuss our results.

5.3.1 Event study evidence

We start by exploiting the staggered entry of public pharmacies in an event study framework. For this analysis, we use IQVIA data on drug prices and sales across local markets. A challenge for combining data on entry of public pharmacies with data from IQVIA is that the level of geographic aggregation of the latter is in some cases larger than counties, which is the level at which public pharmacies operate. To tackle this issue, we estimate a stacked event study regression.[14] Whenever a location has more than one event, we create as many copies of the data as the number of events. We stack the copies in a dataset and use the entry of public pharmacies to all counties within a location as events. Figure A.4 shows the distribution of the number of events per local market.

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

The main specification we estimate takes the following form:

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

where g indexes entry events within a local market. The dependent variable y_{mlgt} is either logged drug prices or logged drug sales for molecule m in local market l in month t.[15] Our interest is in the coefficients β_k on the dummies $D^k_{lgt} = 1\{t = e_{lg} + k\}$, which indicate whether a month t is exactly k months after event time e_{lg} for event g in local market l. We normalize $\beta_{k=-1} = 0$, so we interpret all coefficients β_k as the effect of a public pharmacy opening on the dependent variable exactly k months after its entry. The specification also includes molecule-month fixed effects λ_{mt} to account for time varying unobservables at the level of molecules, and molecule-location-event fixed effects θ_{mlg} to account for persistent differences in market conditions across local markets. Standard errors are clustered at the molecule-location level.[16]

The entry of public pharmacies had meaningful effects on private pharmacies. Figures 5-a and 5-b present the results for sales and prices respectively. Drug sales by private pharmacies decrease after a public pharmacy enters a location. Our estimates imply that 15 months after the entry of a public pharmacy, private pharmacies in that market sell around 3 percent less. Furthermore, drug prices in private pharmacies increase by 1 percent 15 months after the entry of a public pharmacy.[17] Both effects increase over time, suggesting that public pharmacies evolve in terms of enrolling more consumers and possibly improving their product offerings and convenience.

The main threat to the identification of the effect of public pharmacies is reverse causality.

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

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

[17] There is limited cross-sectional variation in prices across locations, in line with recent evidence from other contexts (Adams and Williams, 2019; DellaVigna and Gentzkow, 2019). This limits the extent to which we expect to find price effects. Moreover, our research design is only able to identify price effects stemming from variation across local markets, and thus any market-wide price effects across locations are not captured by our empirical strategy.

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 suggests that reverse causality and strategic considerations do not play a significant role in our setting.[19]

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

5.3.2 Main results

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

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

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

The main results are similar to those in the event study framework, as shown by Table 4. The entry of public pharmacies decreases drug sales by private pharmacies by 4 percent and increases drug prices by private pharmacies by 1.1 percent.[20,21]

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

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

[20] For robustness, we report estimates of equation (3) using exposure to the first public pharmacy only in Table A.5, for which results are almost the same. Additionally, we confirm the statistical significance of results using randomization inference (Imbens and Rubin, 2015). See Figure A.7.

[21] We provide additional results on price effects in Appendix B.2. In particular, we provide results from a de-

The effects of public pharmacies on private pharmacy sales are stronger for molecules associated with chronic conditions. Column 3 in Table 4 shows a decrease in sales of 5.4 percent for such molecules, and a decrease of only of 2 percent for molecules associated with non-chronic conditions. This finding is consistent with public pharmacies mostly focusing on drugs related to chronic conditions. Moreover, it is consistent with our experimental evidence showing that households with members with chronic conditions react more strongly to the availability of public pharmacies in terms of shopping behavior. For prices, column 6 in Table 4 shows, in contrast, that the effect is somewhat smaller for molecules associated with chronic conditions.[22]

5.3.3 Discussion

The entry of public pharmacies had equilibrium effects on private pharmacies. As expected due to the lower prices offered by public pharmacies, some consumers substituted away from private pharmacies and drug sales in the latter decreased. While increased competition could have induced private pharmacies to reduce drug prices, we find that private pharmacies instead increased prices. This response is consistent with the price sensitivity effect of entry dominating the market share of entry. In particular, while some consumers switch to public pharmacies upon their entry, it must be that those had a relatively low willingness to pay for private pharmacies, which led to the residual demand of private pharmacies to become steeper. The increase in private pharmacy prices that we estimate implies that the upward pricing pressure from the latter was larger than the downward pricing pressure from overall substitution towards public pharmacies.[23,24]

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composition developed by Atal et al. (2019) for the effects of public pharmacies on average paid prices for drugs in molecule-location. Average paid prices increased by 1.7 percent following the entry of public pharmacies, such that price changes by private pharmacies were indeed the main driver of such change. The remainder of the increase in average paid prices is driven mostly by entry of relatively expensive drugs after the entry of public pharmacies.

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

[23] In our model in Appendix A, we show that a key condition under which private pharmacy prices are more likely to increase is a negative correlation in consumer willingness to pay for public and private pharmacies, such that consumers who have a high valuation for private pharmacies also have a low valuation for public pharmacies. This negative correlation implies that consumers who substitute away from the private pharmacy upon entry are those with low willingness to pay for the private pharmacy—and thus the most price sensitive—which leads to the residual demand curve of the public pharmacy to be steeper after entry. In addition, there must be enough heterogeneity in willingness to pay across consumers, as otherwise there is no scope for increasing prices substantially. Figure A.12 shows simulation results that illustrate that the direction of the price effects of entry indeed depends on these parameters of the distribution of consumer preferences.

[24] 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".

The sales response to the entry of public pharmacies may seem small given the magnitude of the price differences between public and private pharmacies. Our interpretation is that product differentiation plays a role in mediating this response. As documented above, public pharmacies are less convenient than private pharmacies in terms of waiting times, opening hours, product variety, and travel distance. The lack of a stronger response suggests that a sizable share of consumers value those attributes enough as to not substitute towards public pharmacies on the basis of lower prices. Higher quality public pharmacies would have likely led to stronger equilibrium responses.[25] Second, our event study results in Figure 5 show that both quantity and price effects increase over time, suggesting that the full effects once the market settles on a new equilibrium may be larger.

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

6 The benefits and costs of public pharmacies

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

[25] We illustrate the role of vertical differentiation between private and public pharmacies using our model in Appendix A. Our model simulations show that vertical differentiation indeed influences the extent to which the entry of public pharmacies affect private pharmacy prices and market share depends on vertical differentiation. Figure A.13-a shows that the extent of business stealing by an entrant decreases substantially as the quality of the entrant relative to the incumbent decreases. Moreover, Figure A.13-b shows that the incumbent in the market is able to sustain higher prices when the quality of the entrant relative to the incumbent is lower.

6.1 Municipal finance and the cost of public pharmacies

Given that public pharmacies were created by local governments that manage multiple other local services, it is important to understand whether these are economically sustainable or represent a financial burden that may crowd-out other services. To study this margin, we exploit administrative data from municipal finances to estimate the financial impacts of public pharmacies.[26]

For this analysis, we estimate the following regression:

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

where y_{ct} is a financial outcome in county c and year t (e.g., spending in health services), PP_{ct} indicates the period after the entry of a public pharmacy in county c. The specification includes county and year fixed effects. In terms of data, we observe annual county spending and revenue for 2013–2019. Both spending and revenue have subcategories that we aggregate into health and non-health categories. To ease the comparison across counties, we use the log spending and revenue per capita as dependent variables in this analysis.[27]

Table 5 presents these results. These estimates deliver two main results. First, the entry of public pharmacies are associated with an increase of 5.1 percent in health spending in column 1, that is somewhat compensated by an increase in health revenue of 3.8 percent in column 2. The difference between these effects is statistically significant, with a p-value of 0.066. Second, we do not find strong evidence suggesting that public pharmacies affect non-health services in columns 3 and 4. While our point estimates imply that spending in non-health services decreases more than its revenue, those coefficients are not statistically significant. In terms of overall municipal finance, our point estimates in columns 5 and 6 imply that spending increases more than revenue, although those coefficients are again not statistically significant. Put together, this evidence suggests that the higher deficit in health services induced, if any, only a slight amount of crowd-out of other municipal services and a small increase in the overall municipal deficit.[28]

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

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

[28]Figure A.10 displays the corresponding event study estimates for this specification, which provide reassuring evidence regarding the trends in these outcomes leading to the entry of public pharmacies.

These estimates allow us to compute the average cost of introducing a public pharmacy. Public pharmacy profits depend on the markup they charge on drugs, if any, and any initial investment and operation costs it incurs. The fact that public pharmacies induce a deficit implies they set prices below average cost. The average spending and revenue per capita in health services are $164.7 and $163.1. The average county in the country has a population of 52,325. Combining these basic statistics with our estimates in columns 1 and 2 of Table 5, we calculate that the annual loss of the public pharmacy in the average county is $115,037.[29] In the next sections, we compare this cost estimate with the estimated benefits of public pharmacies for consumers.

6.2 Lack of health effects of public pharmacies

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

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

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

Our estimates provide no evidence that public pharmacies improved health outcomes in the short run, as measured by avoidable hospitalizations. Table 6 displays these results. For each outcome, we show results for all individuals and for individuals under public insurance (*Fondo Nacional de Salud*, FONASA), which are on average of lower income and more likely to benefit from the public pharmacy. Across all outcomes and samples, we find no statistically significant effect of the entry of a public pharmacy to a local market. That said, our estimates are not precise enough as to rule out effects that could be quantitatively meaningful. In particular, our estimates can reject at the 5 percent level reductions of 1.07 hospitalizations, 9.68 hospitalization days, 0.13 surgeries, and 0.03 deaths per 100,000 inhabitants as the effect of public pharmacies, which are equivalent to reductions of 4–7 percent in these outcomes relative to their baseline levels.[30]

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

6.3 Comparing costs and benefits

In this section, we use our previous results to compare the benefits and costs of public pharmacies. Our measure of benefits from public pharmacies focuses on reduced expenditure in drugs for consumers, given that we find no evidence of health effects. We develop a simple accounting framework to estimate effects on consumer expenditure by combining our results on economic effects from section 5 with basic statistics from the market.

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

[30]Figure A.11 shows results from an event study version of equation (4). For all outcomes and samples, we again find no evidence that public pharmacies affected health outcomes. Reassuringly, these results show a lack of differential trends across counties leading to the entry of public pharmacies, which provides evidence against reverse causality.

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

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

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

$$\Delta e = \underbrace{M p_0^r}_{\substack{\text{Baseline}\\ \text{expenditure}}} \times [\underbrace{(1 - \beta_s)(1 + \beta_p) - 1}_{\substack{\Delta \text{ expenditure}\\ \text{in private pharmacies}}} + \underbrace{\beta_s \phi_1^u (1 + \beta_p)}_{\substack{\Delta \text{ expenditure}\\ \text{in public pharmacy}}}]$$

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

The average consumer saves US\$3.3 per year according to these estimates. This average masks substantial heterogeneity: those who stayed at private pharmacies increased their annual spending by \$2.3, whereas those who switched to the public pharmacy reduced it by \$140. A population of particular interest is that of consumers with chronic conditions, who are the main target of public pharmacies and account for 22 percent of the population according to the 2016–2017 ENS. Our estimates imply that these consumers decreased their yearly expenditure by an average of \$22.3. Among them, those who stay with private pharmacies increase their yearly expenditure by \$6.5, whereas those who switch decrease it by \$537.8. To put these numbers in context, the median monthly wage among working-age individuals is around \$670. Adding up across consumers, these estimates imply that consumers in the average county decrease their aggregate spending by \$175,181 per year. If all counties in the country introduced public pharmacies, aggregate spending would decrease by \$60,262,544 per year, equivalent to 1.6 percent of total expenditure according to the EPF. Accounting for equilibrium price responses by private pharmacies is quantitatively relevant. Omitting them would lead to overestimating the reduction in expenditure by 68 percent.

Our estimates imply that consumer benefits in terms of reduced drug expenditure on infra-

marginal units are 52 percent higher than the cost of public pharmacies. Public pharmacies achieve reductions in consumer expenditure higher than their costs because of two reasons: public pharmacies hold a cost advantage relative to private pharmacies when purchasing from laboratories, and private pharmacies hold substantial market power in the retail market (FNE, 2019). Public pharmacies thus deal with two salient market failures in this industry. Because of this, the introduction of a public firm likely performs better than an alternative policy of subsidizing drug purchases. In this simple framework, the cost of a subsidy is the reduction in drug expenditure, and is thus higher than that of the public pharmacy according to our estimates. This is because subsidies are able to reduce drug expenditure, but do not deal with market power in the private market, and therefore must incur a higher cost to achieve the same effects as the public pharmacy.[31]

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

6.4 Political returns of public pharmacies

Budget constraints and electoral incentives are crucial drivers of policy decisions (Besley and Case, 1995; Lizzeri and Persico, 2001; List and Sturm, 2006). Although public pharmacies are relatively low cost and Figure 1 suggests mayors expected political returns, their small negative impact on a large number of people suggests this policy might not be politically profitable. We end the analysis by exploiting experimental variation from our informational intervention along with self reported voting behavior to estimate the causal effect of awareness of public pharmacies among consumers in the pharmaceutical market on political support for the incumbent. Our baseline survey asked about the intention to vote for the mayor in the upcoming local election. Similarly, our follow-up survey asked whether the individual actually voted in the election.

Table 7 presents results from estimating equation (1) for political outcomes. Columns 1 and 4 study self-reported voting behavior. As much as 26-28 percent of the control groups reported to vote for the incumbent, which increases by approximately 6 percentage points for the treatment group. While these point estimates are large in magnitude, they are not statistically significant

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

at conventional levels, with p-values of 0.21 and 0.12. To increase the precision of the analysis, columns 2 and 5 control for the intention to vote for the mayor at baseline along other covariates, and include county fixed effects. Treatment effects using this specification remain similar in magnitude but indeed become more precise, with p-values of 0.06 and 0.11.[32]

Effects on voting behavior are concentrated among individuals from households with members with chronic conditions. Columns 3 and 6 explore these patterns of heterogeneity. Households with someone with a chronic condition report having voted 8 percentage points more for the incumbent, larger than the 2-7 percentage points higher vote share among treated households without a chronic condition. Although the small sample prevent us from rejecting the null of a similar impact across these groups, the result is consistent with the 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 the awareness about public pharmacies and their characteristics increased consumers support for the incumbent mayor.

We combine these results with estimates of consumer savings from section 6.3 to estimate the political returns of public pharmacies. The experiment suggests that introducing a public pharmacy increases the number of votes for the incumbent by 1,055, relative to an average of 16,105 total votes across counties in the 2012 local election. Our estimates of effects on drug expenditure imply that the incumbent obtains 1 additional vote per $166 of yearly consumer savings. Consider the monthly savings of consumers who switch to public pharmacies and focus on consumers with chronic conditions. Within that population, the average individual gets monthly savings of $44.8. These "transfers" increased the political support of the incumbent mayor by 8.1 percentage points. For reference, Manacorda et al. (2011) find that a targeted monthly transfer of $70 increased the political support of the incumbent government by 11 percentage points in Uruguay.

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

7 Conclusion

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

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

The political rewards of public firms could be interpreted as showing that, as a whole, public firms increased welfare. However, we highlight the fact that recent research shows that people may over-value policies when they do not internalize the general equilibrium effects that affect them (Dal Bó et al., 2018). Our findings are somewhat consistent with this interpretation, as the majority of consumers in the market are worse off after the entry of public pharmacies due to increased private pharmacy prices.[33] These findings highlight the need to evaluate the market effect of policies instead of drawing conclusions on their desirability based on voting behavior.

Our analysis leaves many questions for future research. Of particular relevance is understanding the choice of quality among public firms. If the quality of public firms was higher, we would expect more consumers to switch to them and the stronger the equilibrium effects towards the private sector. However, changes in the quality of public firms could influence their targeting properties by modifying the population that adopts them (Kleven and Kopczuk, 2011). Furthermore, it

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

is also possible that a higher quality of public firms triggers other strategic responses in the private sector. In the context of retail, these could include changes in the location, prices, or quality of private stores. Our findings thus call for attention to how the interplay between public and private firm attributes may shape equilibrium effects in the market and determine the overall and distributional impacts of state-owned firms.

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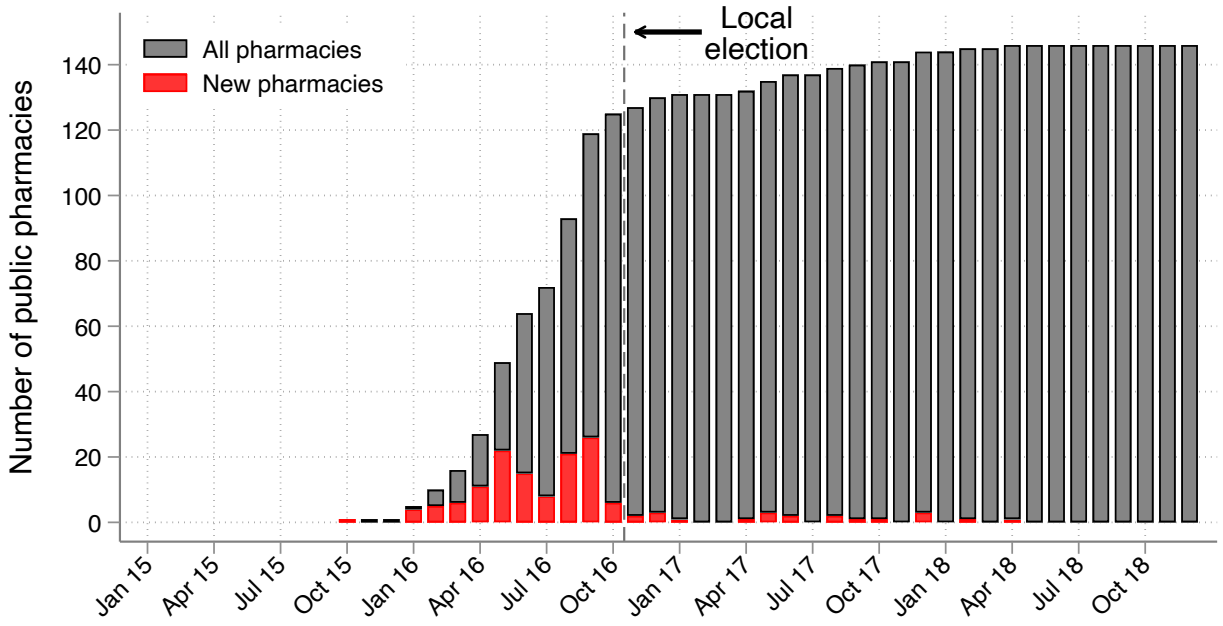
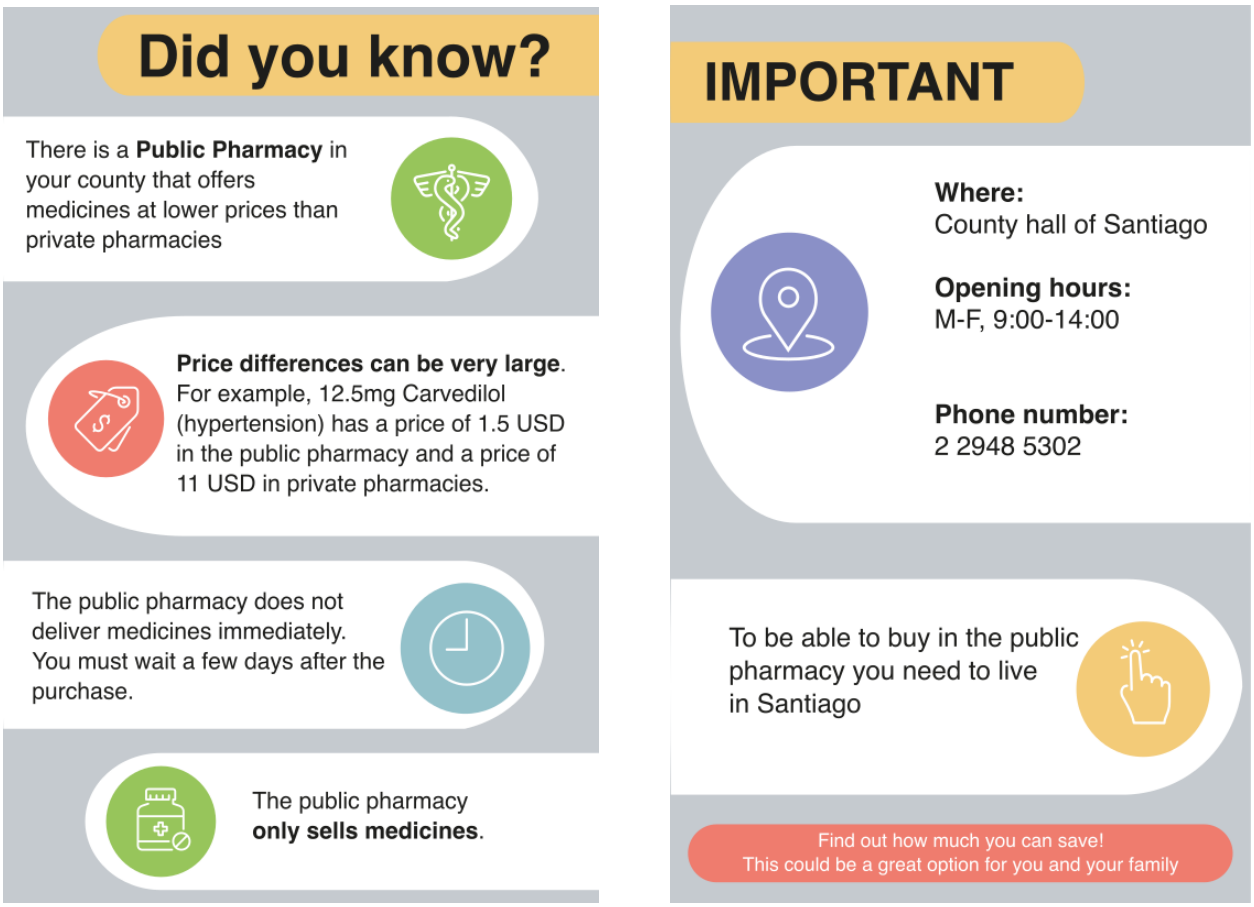
Figure 1: Timing of entry of public pharmacies



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

Figure 2: Informational treatment

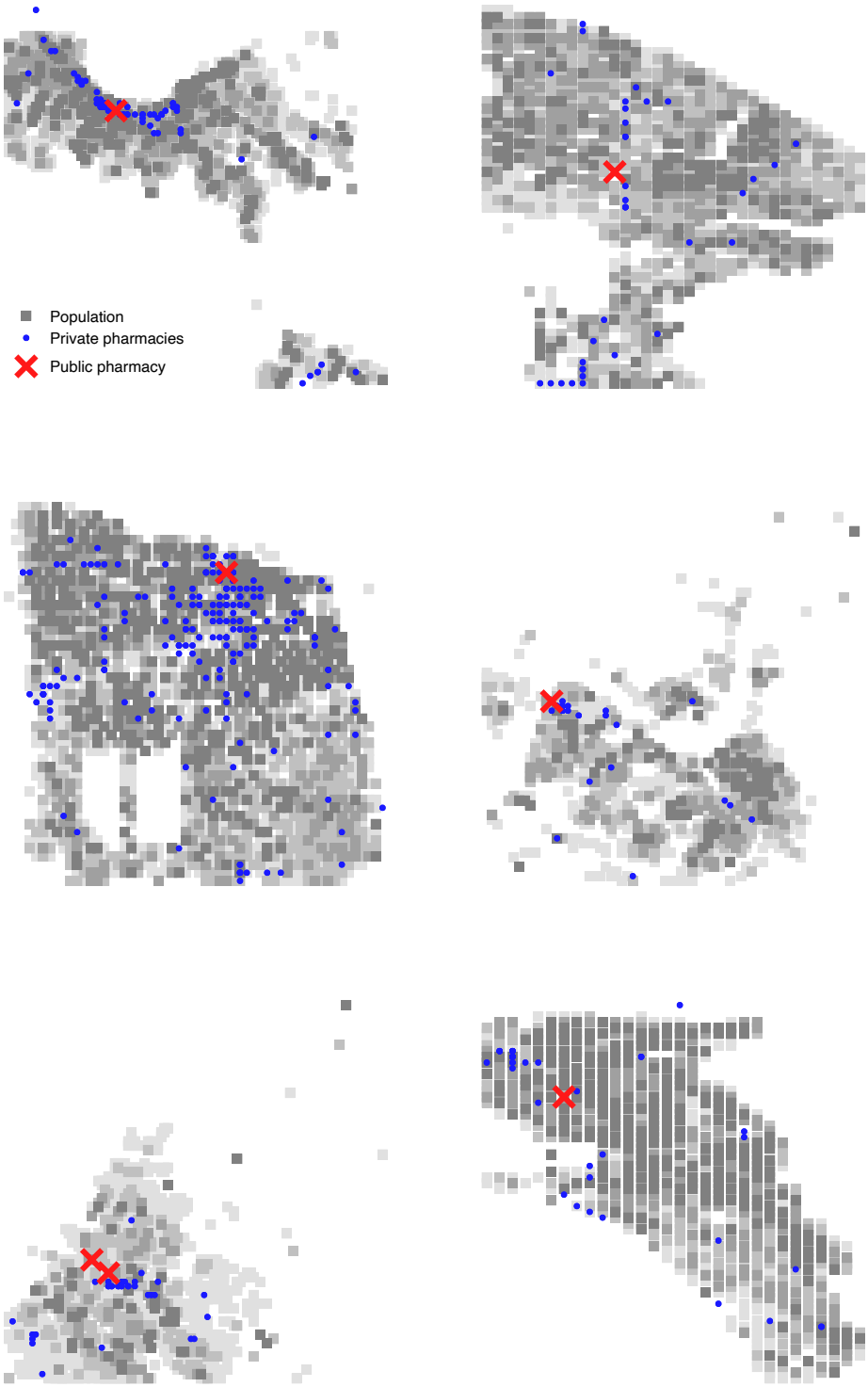


(a) Awareness and convenience

(b) Search details

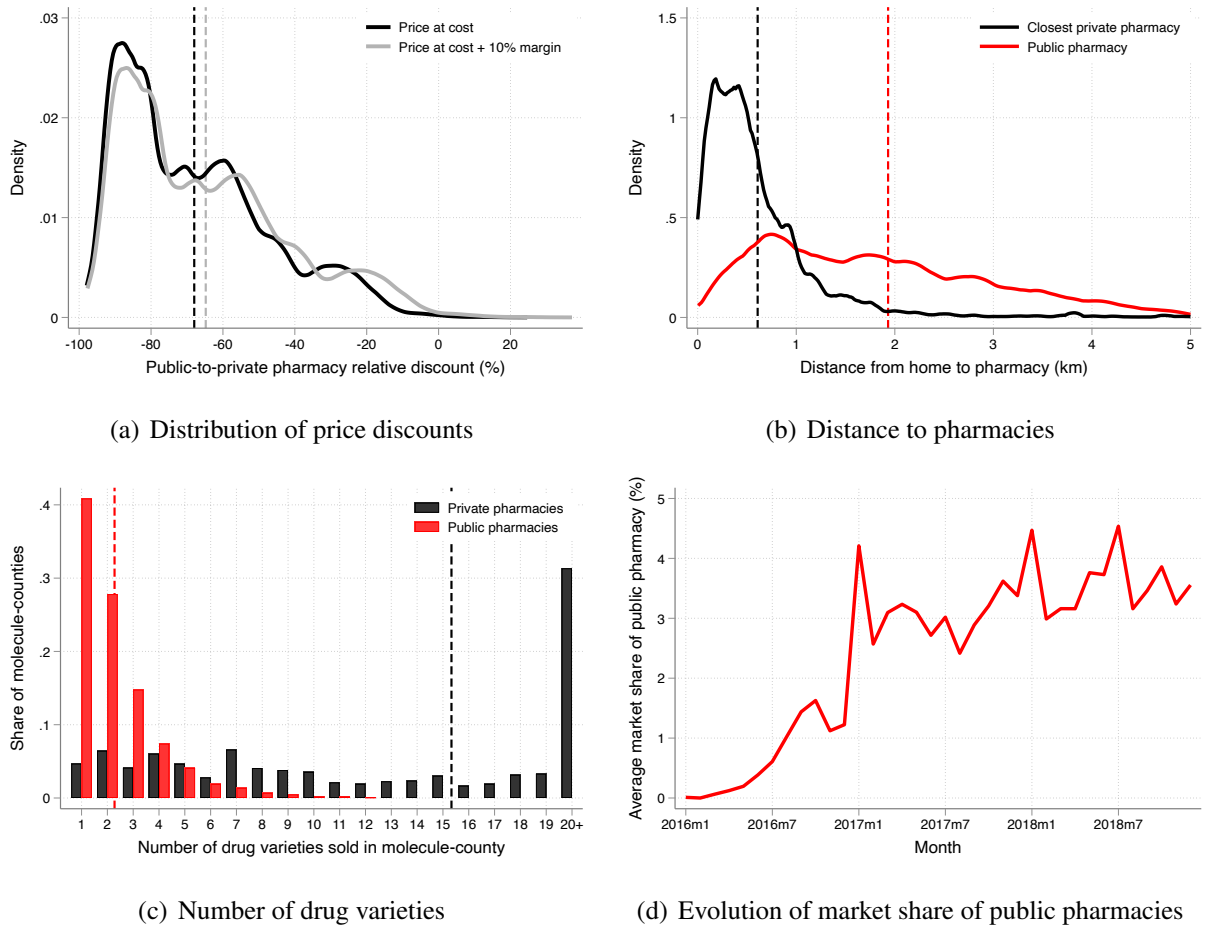
Notes: This figure displays the informational interventions delivered as part of the field experiment. Panel (a) displays the first part of the treatment, which aimed at increasing awareness about the public pharmacy. It introduces the public pharmacy and mentions that it offers lower prices than private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

Figure 3: Locations of public pharmacies in local markets



Notes: Each map displays the geo-coded location of private pharmacies, public pharmacies, and population in local markets (i.e. counties).

Figure 4: Relative prices between private and public pharmacies



(a) Distribution of price discounts

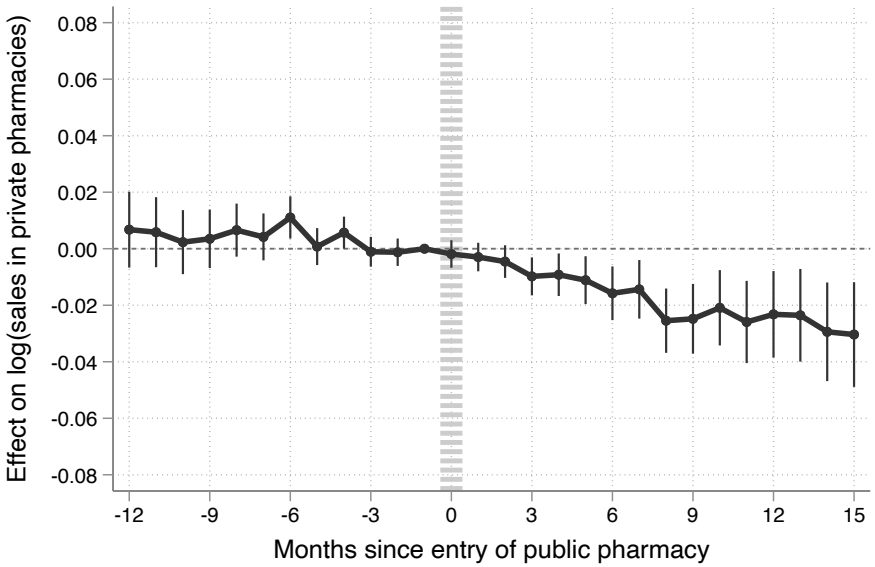
(b) Distance to pharmacies

(c) Number of drug varieties

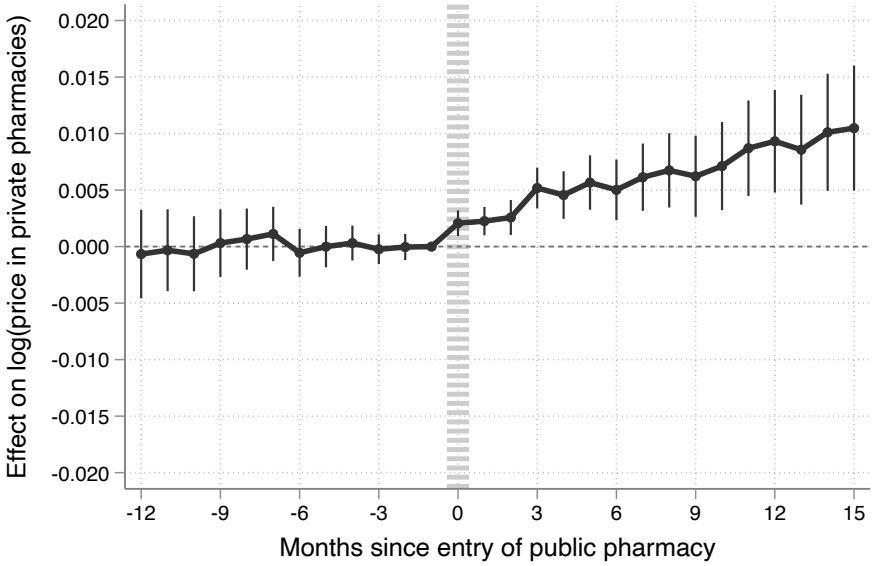
(d) Evolution of market share of public pharmacies

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

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



(a) Sales



(b) Prices

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

Table 1: Balance in covariates between treatment and control group

	(1)	(2)	(3)
Variable	Control	Treatment	p-value $H_0 : (1) = (2)$
Monthly drug expenditure	76.31	76.69	0.94
	(73.54)	(69.97)	
Chronic condition in household	0.57	0.56	0.84
	(0.50)	(0.50)	
Age	45.25	46.32	0.39
	(16.81)	(17.50)	
Education higher than HS	0.54	0.51	0.44
	(0.50)	(0.50)	
Female	0.60	0.63	0.47
	(0.49)	(0.48)	
Public insurance	0.62	0.65	0.37
	(0.49)	(0.48)	
Day with internet (1-7)	5.47	5.23	0.23
	(2.71)	(2.84)	
Day with social media (1-7)	5.37	5.19	0.37
	(2.79)	(2.91)	
Employed	0.62	0.64	0.53
	(0.49)	(0.48)	
Supports incumbent	0.50	0.51	0.86
	(0.50)	(0.50)	
Voted in previous election	0.73	0.74	0.68
	(0.44)	(0.44)	
Knows public pharmacy	0.61	0.67	0.09
	(0.49)	(0.47)	
Perceived relative price of public pharmacy	0.46	0.46	0.96
	(0.18)	(0.23)	
Perceived days to delivery at private pharmacy	8.80	8.35	0.61
	(12.87)	(11.87)	
Observations	319	507	

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

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

	(1)	(2)	(3)	(4)
	County has public pharmacy			
	Yes	No	(1)–(2)	Timing of entry
Pharmacies and hospitals				
Private pharmacies per 100,000 inhab.	13.57	7.71	5.86***	-0.003
Log sales in private pharmacies	15.37	15.15	0.21**	-0.465
Price index in private pharmacies	931	872	59**	0.001
Hospitalizations per 100,000 inhab.	9,430	8,127	1,302***	0.00
Deaths per 100,000 inhab.	208	177	31***	-0.02
Socioeconomic characteristics				
Log household income	12.97	12.61	0.37***	-0.467
Age of inhabitants	44.50	45.68	-1.18***	0.115
Average unemployment rate	0.10	0.09	0.02***	7.091
Share with public health insurance	0.83	0.89	-0.06***	1.400
Self reported health (1-7)	5.54	5.49	0.05*	1.900
Number of doctor visits	0.32	0.30	0.02	1.359
Population (in 10,000)	9.60	1.88	7.72***	-0.425**
Political characteristics				
Number of competitors	3.56	3.20	0.36***	0.121
Winning margin	0.19	0.17	0.02	-3.768
Vote share winner	0.54	0.53	0.01	5.951
Incumbent coalition wins	0.62	0.57	0.05	0.439
Incumbent coalition: independent	0.31	0.35	-0.03	-0.045
Incumbent coalition: left-wing	0.46	0.37	0.10*	-1.161**
Incumbent coalition: right-wing	0.22	0.29	-0.06	–
Number of counties	147	197	–	147

Notes: Counties with and without public pharmacy until July 2018. "Pharmacies and hospitals" are own construction using data from the Public Health Institute and IQVIA in 2014. "Socioeconomic characteristics" are own construction using data from the 2015 National Socioeconomic Characterization. "Political characteristics" are own construction using data from Chile's Electoral Service. Column 4 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. Significance level in columns 3-4: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Experimental results for economic outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A - Knowledge about public pharmacies								
	1(Knows about pharmacy)			log(Perceived price)			log(Perceived waiting time)		
Treatment	0.099***	0.069***		-0.117**	-0.094**		0.173	0.188*	
	(0.034)	(0.026)		(0.046)	(0.045)		(0.107)	(0.103)	
Treatment × chronic			0.032			-0.114*			0.134
			(0.033)			(0.061)			(0.140)
Treatment × non-chronic			0.126***			-0.063			0.264*
			(0.042)			(0.065)			(0.151)
Dependent variable at baseline		0.489***	0.488***		0.382***	0.382***		0.397***	0.399***
		(0.039)	(0.039)		(0.049)	(0.049)		(0.068)	(0.068)
Lee bounds	[-0.018, 0.134***]			[-0.236***, -0.020]			[0.049 , 0.189]		
p-value for H_0: $\beta_C = \beta_{NC}$	-	-	0.080	-	-	0.570	-	-	0.531
Mean for control group	0.773	0.773	0.773	9.070	9.070	9.070	1.387	1.387	1.387
Observations	514	514	514	498	491	491	445	425	425
R-squared	0.017	0.474	0.477	0.012	0.197	0.197	0.006	0.181	0.182
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
	Panel B - Usage of public pharmacies								
	1(Enrolled)			1(Purchased)			Probability of usage		
Treatment	0.018	0.020		0.019	0.023		0.060*	0.054	
	(0.024)	(0.024)		(0.017)	(0.018)		(0.035)	(0.036)	
Treatment × chronic (β_C)			0.032			0.043*			0.085*
			(0.033)			(0.024)			(0.046)
Treatment × non-chronic (β_{NC})			0.002			-0.008			-0.008
			(0.034)			(0.026)			(0.057)
Knows pharmacy at baseline		0.050**	0.050**		0.015	0.015		-0.042	-0.045
		(0.021)	(0.021)		(0.017)	(0.017)		(0.043)	(0.043)
Lee bounds	[0.007, 0.087***]			[0.015, 0.047***]			[0.060 , 0.083]		
p-value for H_0: $\beta_C = \beta_{NC}$	-	-	0.524	-	-	0.155	-	-	0.213
Mean for control group	0.069	0.069	0.069	0.028	0.028	0.028	0.540	0.540	0.540
Observations	514	514	514	514	514	514	387	387	387
R-squared	0.001	0.021	0.100	0.002	0.008	0.067	0.008	0.008	0.057
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+sales)			log(price)		
Public pharmacy index	-0.038***	-0.041***		0.008***	0.011***	
	(0.011)	(0.006)		(0.003)	(0.001)	
	[0.009]	[0.010]		[0.004]	[0.006]	
Public pharmacy index × chronic (β_C)			-0.055***			0.008***
			(0.007)			(0.002)
			[0.012]			[0.005]
Public pharmacy index × non-chronic (β_{NC})			-0.020**			0.015***
			(0.009)			(0.003)
			[0.011]			[0.007]
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. We also provide standard errors clustered at the location level, and are displayed in square brackets.

Table 5: Municipal finance

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

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

Table 6: Effect on avoidable hospitalizations associated to chronic diseases

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

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

Table 7: Experimental results for political outcomes

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

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

ONLINE APPENDIX

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

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

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A Model

In this section, we develop a simple model of consumer choice and firm competition based on Chen and Riordan (2008). The goal is to illustrate the conditions under which entry of an additional firm to a market induces an increase or a decrease in the prices set by an incumbent firm. The environment is simple, but captures several features of our setting.

A.1 Setup

Environment. There is a population of consumers of size one, that faces the discrete choice problem of purchasing from the incumbent, purchasing from the entrant, or not purchasing at all, which is the outside option. We denote these options by $j \in \{I, E, O\}$ respectively. After normalizing the value of the outside option to 0, the value that consumer i gets from each option is:

$$\begin{aligned} u_{iI} &= v_{iI} - p_r \\ u_{iE} &= v_{iE} - p_u \\ u_{iO} &= 0 \end{aligned}$$

where v_{ij} is the willingness to pay and p_j is the price of each option. Willingness to pay v_i is drawn from a differentiable joint distribution $H(v)$, and may feature average differences across firms, may be heterogeneous across consumers within each firm, and may be correlated across firms. Consumers choose the option that gives the highest utility, so that the probability that consumer i choose option j is:

$$\sigma_{ij} = P(u_{ij} \geq u_{ik} \quad \forall k)$$

which induces demand functions:

$$s_j = \int \sigma_{ij} h(v) dv$$

which naturally depend on the set of firms in the market.

On the supply side, the incumbent firm I chooses p^I to maximizes profits $s_I(p_I - c_I)$, which leads to an optimal monopoly price p_I^m before entry, and an optimal duopoly price p_I^d after entry.

The entrant firm is meant to capture public pharmacies in our setting. As such, we assume it sets prices at marginal cost to satisfy a break even condition, which is $p_E^d = c_E$.[34]

A.2 When does entry increase prices?

The net price effects of entry depend on the the relative importance of two competing forces: (i) the extent of substitution away from the monopolist, which imposes downwards pressure on the incumbent price, and (ii) the extent to which demand faced by the monopolist becomes steeper after entry, which imposes upwards pressure on the incumbent price. To establish this intuition formally, we define $F(v_I)$ as the marginal distribution of willingness to pay for the incumbent, and $G(v_E|v_I)$ as the distribution of willingness to pay for the entrant conditional on that for the incumbent. Both of these distributions are defined under the joint distribution $H(v)$. With this notation, we can restate Theorem 1 in Chen and Riordan (2008), which establishes that—under a few fairly general assumptions—the incumbent price will increase upon entry if and only if:

$$\int_{p_I^m}^{\infty} [G(v|v) - G(p_I^m|v)] f(v) dv \leq (p_I^m - c_I) \int_{p_I^m}^{\infty} [g(p_I^m|v) - g(v|v)] f(v) dv$$

and will otherwise decrease.

This condition compares the magnitude of the two effects of entry. The left hand side of the equation is the *market share effect* of entry. This term measures the difference between the market share that the incumbent gets from charging the monopoly price as a monopoly and as a duopoly, that is, before and after entry. The more market share the entrant takes away from the incumbent, the stronger the incentives the incumbent has to decrease price in response to entry. The right hand side of the equation is the *price sensitivity effect* of entry. The magnitude of this effect depends on the difference between the slope of the residual demand curve that the incumbent faces before and after entry. The steeper the demand curve is after entry relative to before entry, the lower the extent of substitution away from the incumbent from marginal consumers upon entry, and therefore the stronger the incentive of the incumbent to increase price upon entry.

The relative strength of these effects will largely depend on the distribution of consumer preferences. For example, the likelihood of a price increase is higher with a negative correlation in willingness to pay. In this case, substitution towards the entrant is lower than under a distribution of preferences with positive correlation. Moreover, those who substitute away from the incumbent

[34] All results hold for the case in which the entrant sets a profit-maximizing price.

are consumers with relatively low willingness to pay for the incumbent among those who purchase from the incumbent before entry, which leads to a steeper residual demand curve after entry.

A.3 Simulation

In this section, we show the results of simulating the a calibrated model. The goal is to show numerically how different parameter combinations yield different predictions regarding the sign of the price effect of entry.

Specification. A key input in the simulation is the joint distribution of willingness to pay for the firms in the market, H_v, which we assume follows a joint normal distribution:

$$\begin{pmatrix} v_I \\ v_E \end{pmatrix} \sim N\begin{pmatrix} \delta_I \\ \delta_E \end{pmatrix}, \begin{pmatrix} \sigma_I^2 & \rho\sigma_I\sigma_E \\ \rho\sigma_I\sigma_E & \sigma_E^2 \end{pmatrix}$$

where the mean willingness to pay for each firm is denoted by δ_I and δ_U. Differences between δ_I and δ_U capture vertical differentiation between firms and relative to the outside option. The dispersion of willingness to pay is captured by the variances σ_I^2 and σ_E^2, and the correlation between the willingness to pay for the incumbent and the entrant is captured by ρ. If the willingness to pay is positively correlated ($\rho > 0$), then consumers share similar preferences for both goods relative to the outside option. If instead willingness to pay is negatively correlated ($\rho < 0$), then consumers with a strong taste for one of the firms have a weak taste for the other firm. This parameter determines the extent to which the slope of demand the incumbent faces changes upon entry, which is key in determining the price effects of entry.

Simulation details. We simulate equilibrium prices and market shares for the environments before and after entry, for a range of parameters of the distribution of preferences. In particular, we set δ_I and δ_E so that $(\delta_I + \delta_E)/2 = 10$ and $\delta_I/\delta_E = k_\delta$ for a a grid of values for k_δ from 1 to 10; we set $\sigma_I = \sigma_E = \sigma$ and construct a grid of values for σ from 1 to 15; and we construct a grid of values for ρ between -1 and 1. We set marginal costs at $c_I = 6$ and c_E. For each combination of (k_δ, σ, ρ), we solve for optimal prices and resulting market shares before and after entry.

A.4 Results

Results on price effects and the distribution of preferences. Our simulations illustrate that consumer preferences over firms play a key role in determining the equilibrium effects of entry on prices. Figure A.12 display results for simulations over a grid of values for heterogeneity in preferences σ and correlation in preferences across firms ρ, for relative mean preferences of $\delta_I/\delta_E = 4$.

These results show two main patterns. First, the price charged by the incumbent firm are more likely to increase when the preferences for the incumbent are more negatively correlated with those for the entrant. A more negative correlation implies that the marginal consumers that substitute towards the entrant are those with low willingness to pay for the incumbent, which makes the residual demand curve of the incumbent steeper and therefore places incentives to increase prices. This is consistent with a stronger price sensitivity effect. Second, the results show that the price charged by the incumbent is more likely to increase when there is more dispersion in preferences, which is partly driven by the fact that when such dispersion is low, the demand curve is flatter and there is limit scope for price increases.

In the context of our setting and empirical results, this simulation suggests that the correlation between preferences for private and public pharmacies is likely negative. This suggests that pharmacy attributes—beyond drug prices—play an important role in pharmacy choice. An attribute that could be important in generating this pattern is heterogeneity in consumer locations relative to pharmacies: consumers who live closer to private pharmacies are likely to pay more for them than for public pharmacies, whereas the opposite may be true for consumers who live closer to public pharmacies.

Results on price effects and the relative quality of the entrant. In addition to studying the conditions under which incumbent prices increase upon entry, we use the model to illustrate the importance of vertical quality difference in determining the penetration of the entrant and the differences in prices between the incumbent and the entrant. Figure A.13 shows results from simulations of the model for a grid of values for relative quality of the incumbent δ_I/δ_E, while keeping average quality across firms fixed. We fix the remainder of the distribution of preferences to values such that the price of the incumbent increases, namely $\rho = -0.99$ and $\sigma = 2.55$.

We study implications of vertical differentiation for market shares and prices. Figure A.13-a shows that while the entrant is able to steal market share from the incumbent, the extent of business

stealing decreases substantially as the quality of the entrant relative to the incumbent decreases. Figure A.13-b shows that the incumbent price is higher when the quality of the entrant relative to the incumbent is lower. Furthermore, these results also show that the price effects of entry on the incumbent price depend on the relative quality entrant. The higher the relative quality of the entrant, the more likely that the incumbent price will decrease upon entry.

These results are consistent with our descriptive evidence and main empirical findings. In section 5.1, we documented that public pharmacies entered the market offering lower quality along several dimensions, which suggests that δ_I/δ_E is relatively large in our setting. These results indeed imply that entrants with low relative quality have low penetration, allow the incumbent to sustain higher prices, and make it more likely for the incumbent to increase prices.

B Additional results on economic outcomes

B.1 Alternative specifications of the event study

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

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

Since there is no obvious way to define unique entry events in our setting, we provide results using two alternative definitions of the event. In the first case, we define the event as the date that a public pharmacy was *first* introduced by a county in a location l. The second definition uses the date that the *largest* county in the location introduced a public pharmacy, among counties for which there is an entry event. Figures A.5 and A.6 display the results for each definition of the event. In both cases, we find no differential pre-trends in sales and prices, and the results are quantitatively consistent with the findings using the stacked event study regression.

B.2 Decomposition of price effects

To further study the effect of public pharmacies on prices, we adapt the decomposition developed by Atal et al. (2019) to our setting. This procedure decomposes the evolution of average paid prices

on terms associated with price changes—the result we report in the main text—, share changes, the correlation between those, product entry and product exit.

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

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

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

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

$$\hat{P}_{mlt} = \hat{P}_{ml0} + \Delta P_{mlt,C} + \Delta P_{mlt,RW} + \Delta P_{mlt,CS} + \Delta P_{mlt,E} + \Delta P_{mlt,X} \tag{5}$$

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

The effect of public pharmacies on average paid prices at private pharmacies is somewhat larger that the on price changes by the latter, discussed in section 5.3. Figure A.8 shows estimates from our event study specification in equation (2) for average paid prices. As for the case of price

changes, these results show a steady increase in prices after the entry of public pharmacies, with no evidence of differential trends leading to that event.

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

Figure A.1: Examples of private and public pharmacy

(a) Outside of private pharmacy

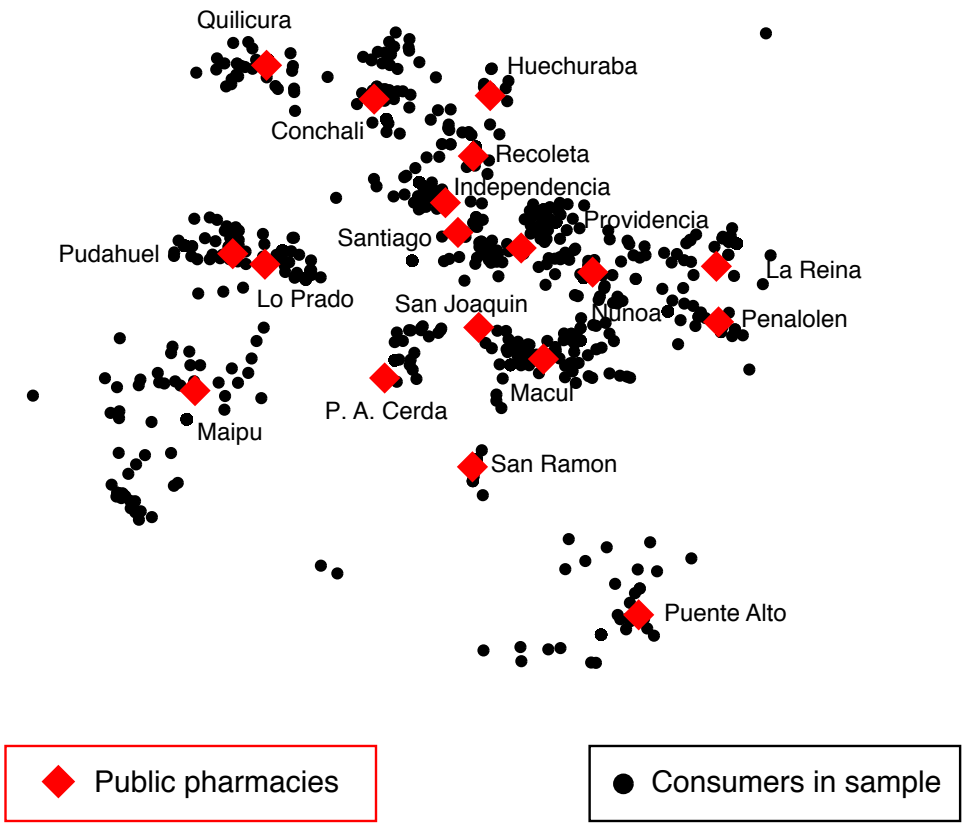
(b) Inside of private pharmacy

(c) Outside of public pharmacy

(d) Inside of public pharmacy

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

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



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

Figure A.3: Timeline of experiment events

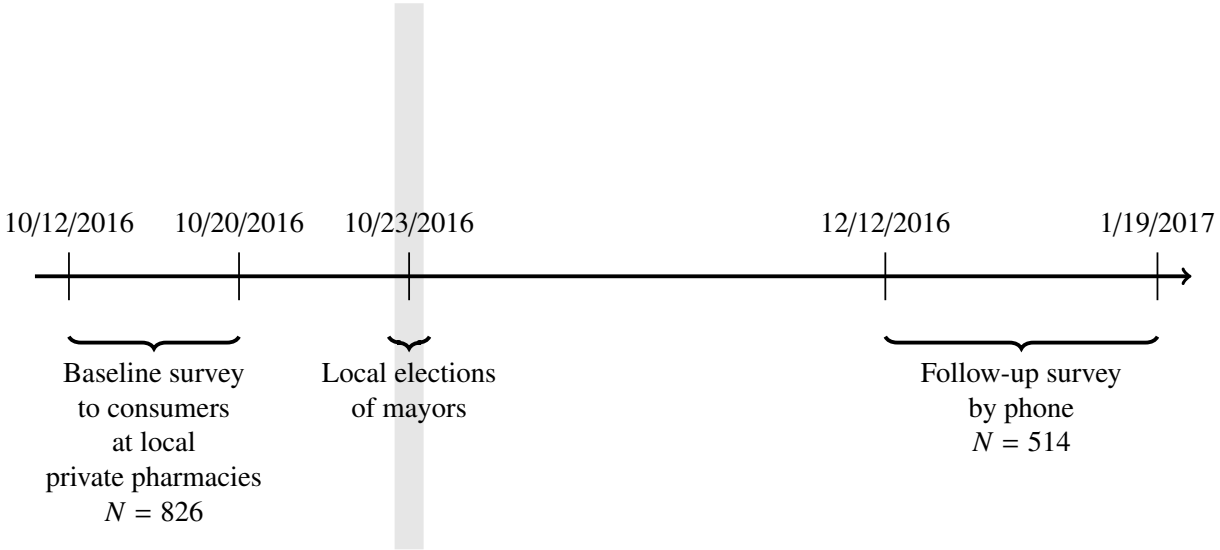
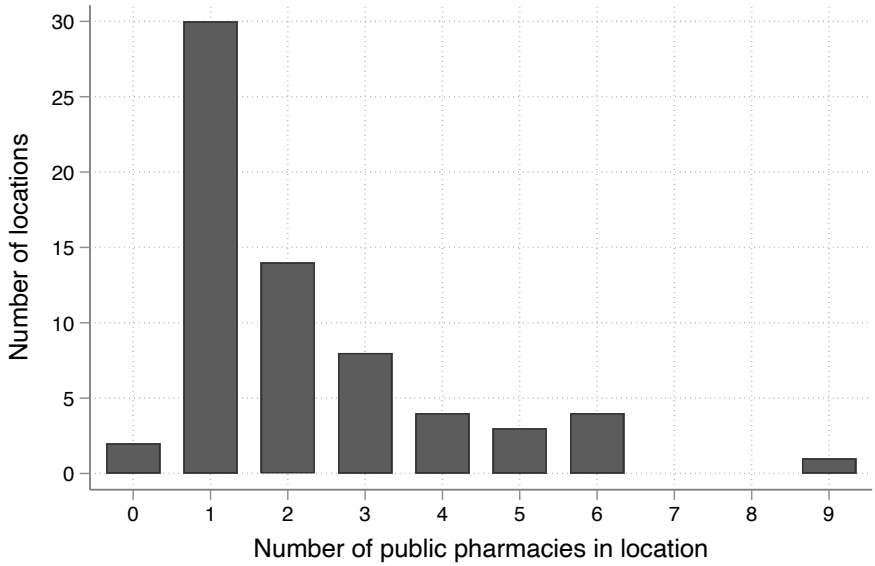
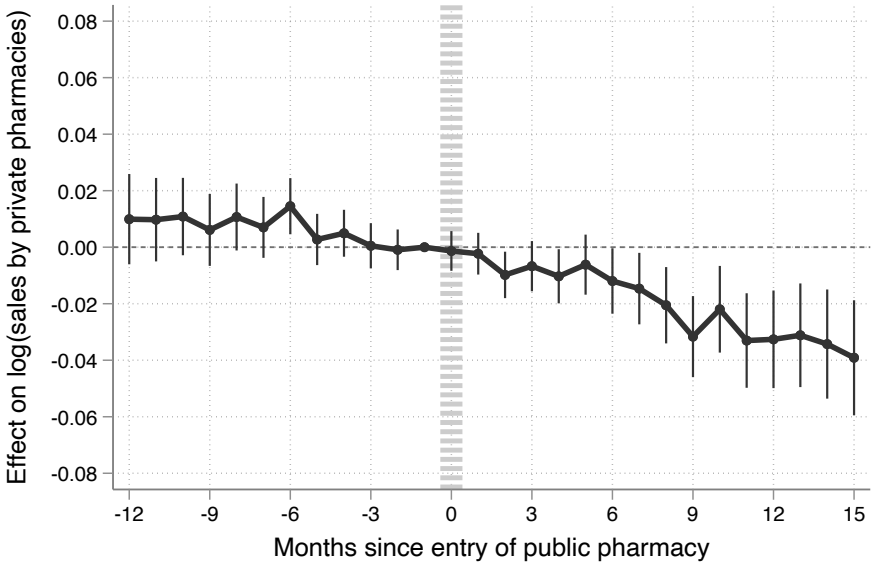


Figure A.4: Impact of public pharmacies: Number of events per location

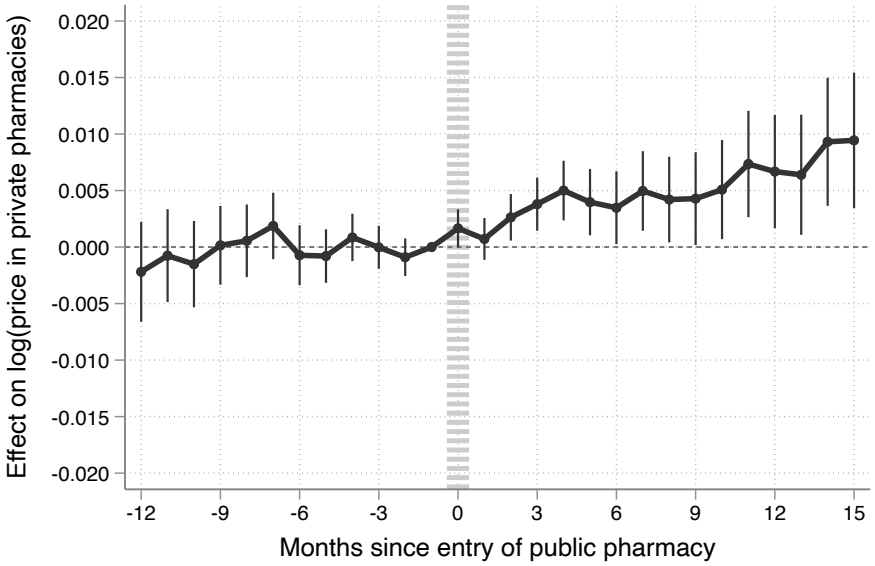


Notes: This figure shows the number of events within a location. An event is defined as the introduction of a public pharmacy in a county,

Figure A.5: Impact of public pharmacies: Entry is first county



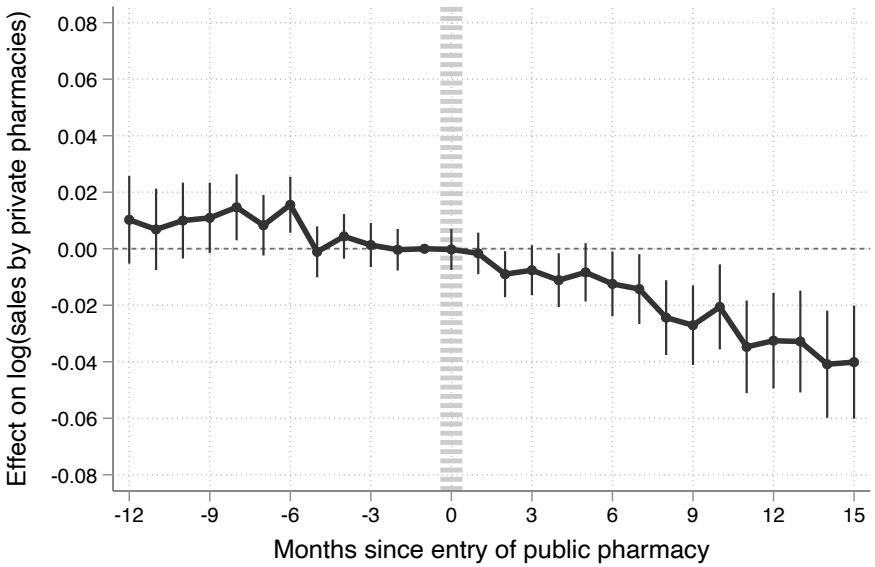
(a) Sales



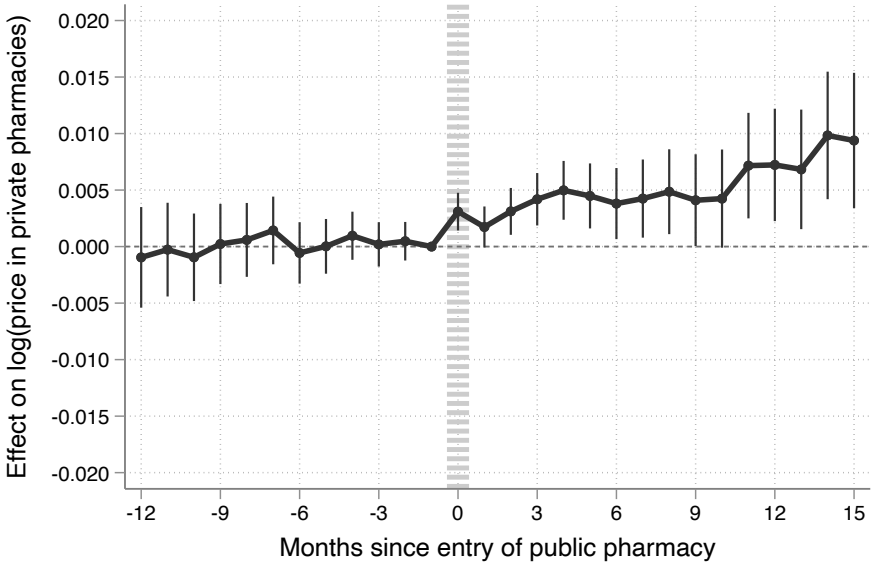
(b) Prices

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

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



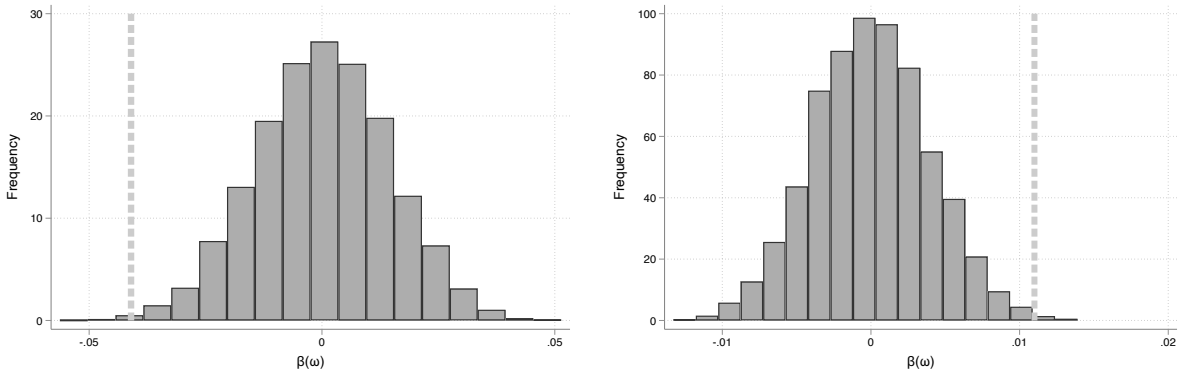
(a) Sales



(b) Prices

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

Figure A.7: Randomization inference for market-level analysis

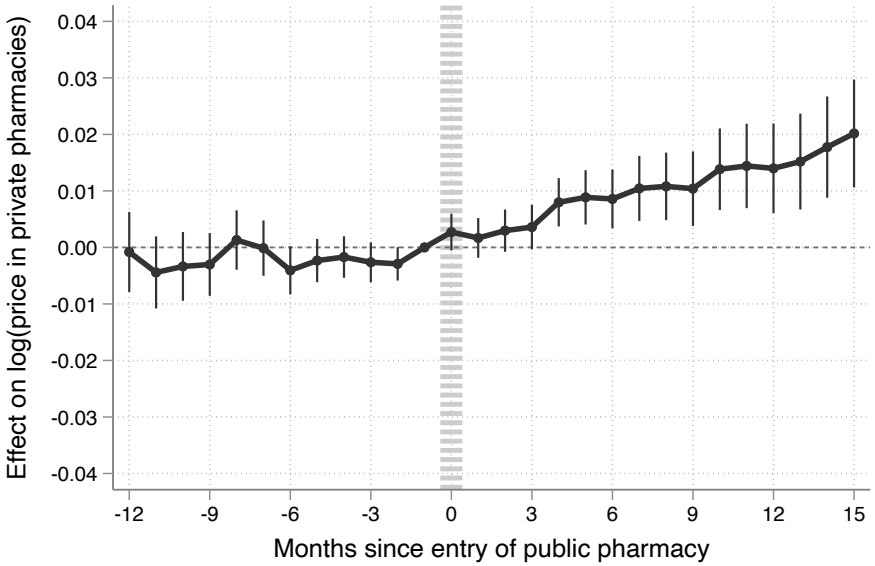


(a) Column 2, sales (p-value<0.01)

(b) Column 5, prices (p-value<0.01)

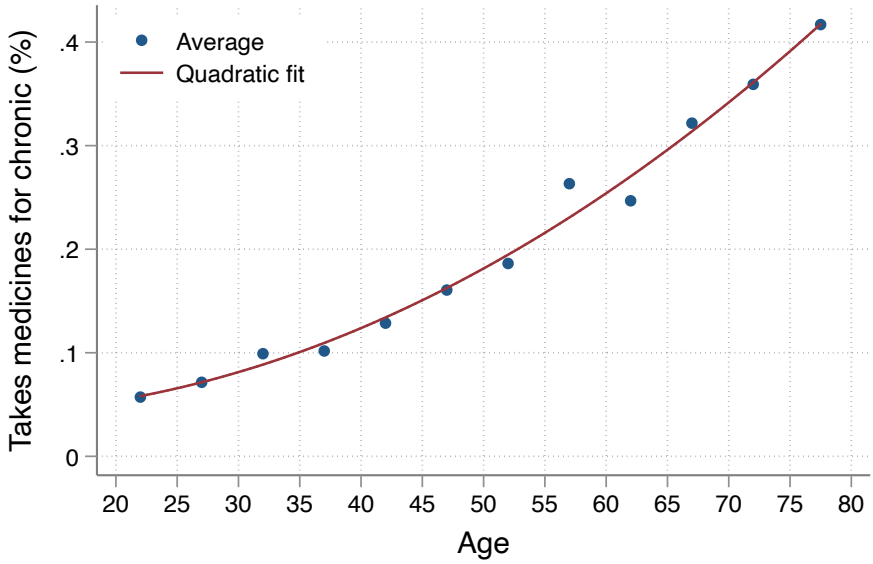
Notes: Each plot presents the distribution of estimates of β in equation (3) after randomizing the location treatment vector. We compute the treatment vectors for all 65 locations, and then randomize them across locations. A treatment vector includes whether the location is treated (i.e., whether a public pharmacy is implemented in the location) and the intensity of treatment (i.e., the share of people in the location with access to a public pharmacy). The vertical line denotes the estimated coefficients in Table 4. We implement the procedure 10,000 times. We compute the one sided test Fisher Exact P-Value (FEP) p-value $\Pr(\beta(\omega) \leq \hat{\beta})$ as the share of draws smaller (larger) or equal to $\hat{\beta}$ in the case of sales (prices) (Imbens and Rubin, 2015).

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

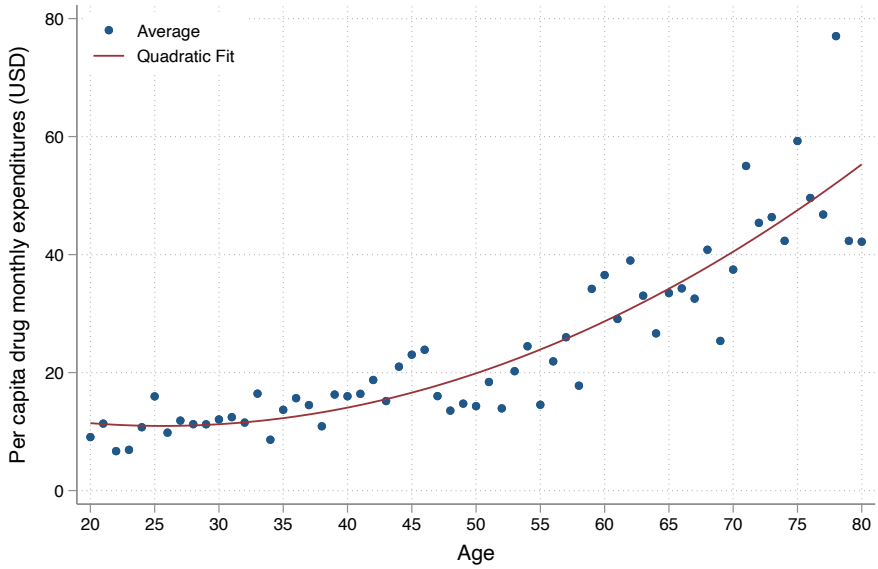


Notes: This figure presents the coefficients of the event study specification in equation (2). The dependent variable measures average paid prices as defined in Appendix B.2. Dots indicate estimated coefficients, and vertical lines indicate the corresponding 95 percent condence intervals.

Figure A.9: Age as a proxy for the likelihood of using the public pharmacy



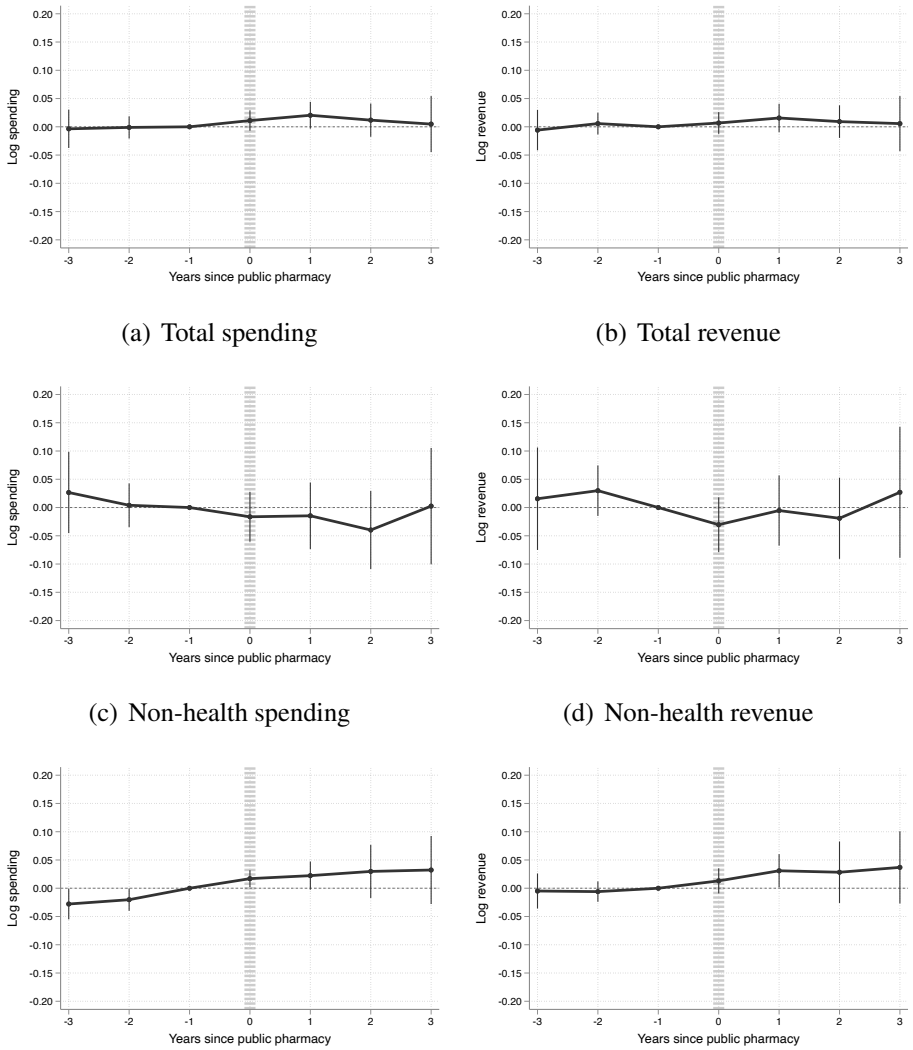
(a) Age and likelihood of chronic disease



(b) Age and drug expenditures

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

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



(a) Total spending

(b) Total revenue

(c) Non-health spending

(d) Non-health revenue

(e) Health spending

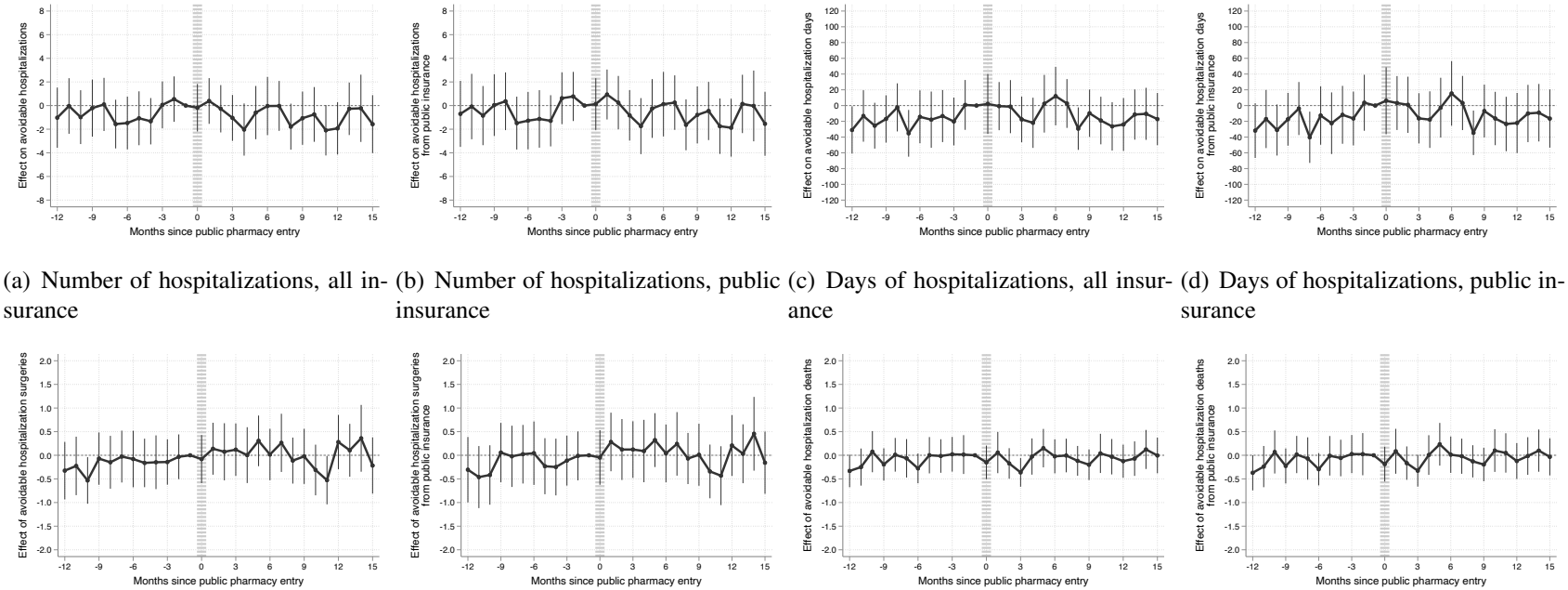
(f) Health revenue

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

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

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

Figure A.11: Event study estimates for effects on avoidable hospitalizations



(a) Number of hospitalizations, all insurance (b) Number of hospitalizations, public insurance (c) Days of hospitalizations, all insurance (d) Days of hospitalizations, public insurance

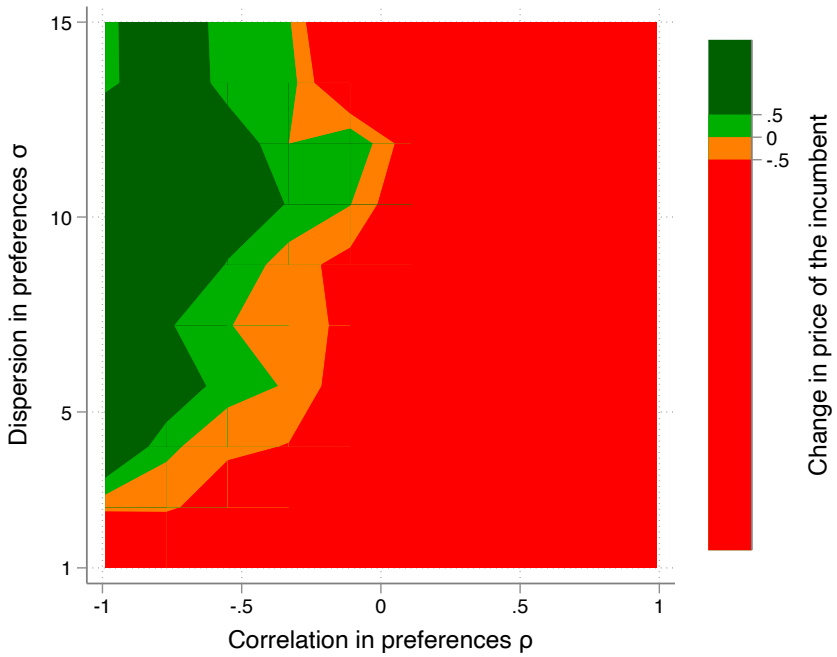
(e) Number of surgeries, all insurance (f) Number of surgeries, public insurance (g) Number of deaths, all insurance (h) Number of deaths, public insurance

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

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

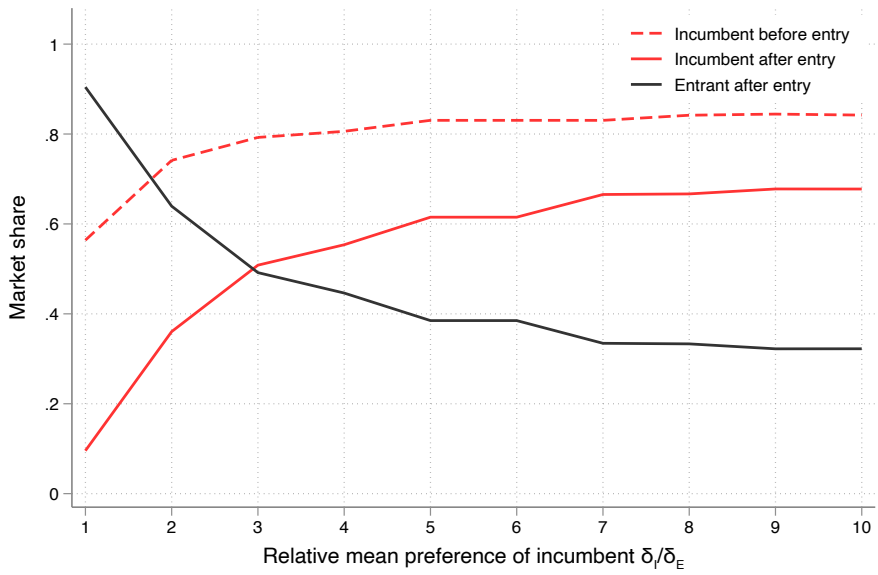
where the outcomes are the same measures of avoidable hospitalization events as in Table 6 and treatment dummies are defined as in equation (2). Each dot is coefficient and vertical lines indicate the 95 percent condence intervals.

Figure A.12: Simulations for the price effects of entry

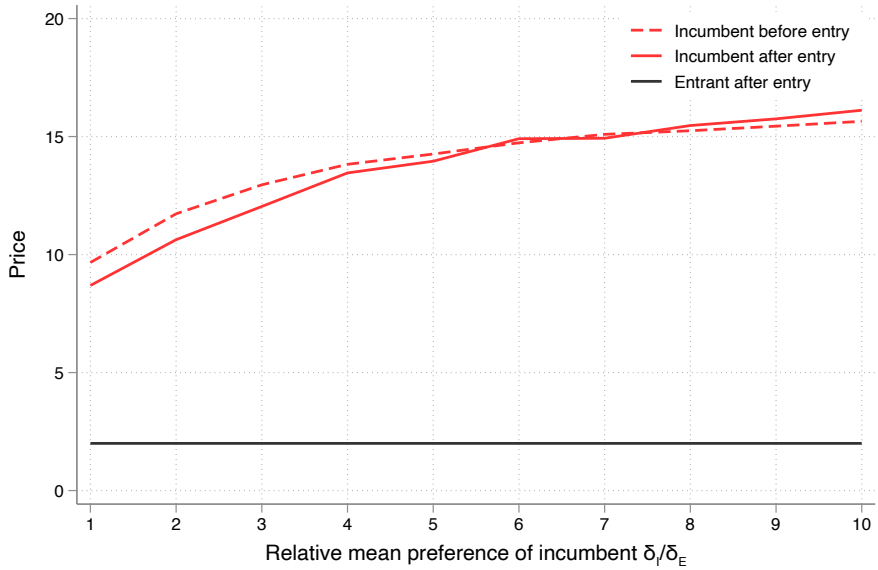


Notes: This figure plots simulated effects of entry on the price that the incumbent charges, as discussed in appendix A. The plot provides results for a grid of values of σ and ρ, under mean preferences for the incumbent and entrant $\delta_I/\delta_E = 4$, although the results are qualitatively similar for different values of the latter. The red region indicates that the incumbent price *decreases*, whereas the green region indicates that the incumbent price *increases* for each distributions of preferences, respectively.

Figure A.13: Simulations for the role of relative quality for equilibrium outcomes



(a) Equilibrium market shares



(b) Equilibrium prices

Notes: Both panels display equilibrium outcomes for the incumbent and entrant, before and after entry for a range of values for relative quality of the incumbent δ_I/δ_E, while keeping the average quality of both firms fixed. Panel (a) displays equilibrium market shares, whereas Panel (b) displays equilibrium prices. Incumbent outcomes are plotted in red, while entrant outcomes are plotted in black. Outcomes before entry are plotted in dashed lines, while outcomes after entry are plotted in dashed lines.

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

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

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

Table A.2: Was a treatment delivered?

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

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

Table A.3: Balance in covariates accross attrition status

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Non-Attrites vs Attriters			Panel B: Non-Attriters		
Variable	Non-Attriters	Attriters	p-value $H_0 : (1) = (2)$	Control	Treatment	p-value $H_0 : (4) = (5)$
Monthly drug expenditure	75.44	78.48	0.57	78.05	73.56	0.54
	(71.93)	(70.37)		(75.50)	(69.31)	
Chronic condition in household	0.61	0.49	0.00	0.61	0.61	0.65
	(0.49)	(0.50)		(0.49)	(0.49)	
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	0.53	0.52	0.89	0.54	0.52	0.72
	(0.50)	(0.50)		(0.50)	(0.50)	
Female	0.64	0.58	0.06	0.62	0.66	0.74
	(0.48)	(0.49)		(0.49)	(0.47)	
Public insurance	0.63	0.66	0.34	0.62	0.63	0.31
	(0.48)	(0.47)		(0.49)	(0.48)	
Day with internet (1-7)	5.26	5.43	0.40	5.12	5.35	0.37
	(2.84)	(2.71)		(2.92)	(2.78)	
Day with social media (1-7)	5.22	5.34	0.56	5.07	5.32	0.17
	(2.89)	(2.82)		(2.96)	(2.83)	
Employed	0.63	0.64	0.74	0.59	0.65	0.82
	(0.48)	(0.48)		(0.49)	(0.48)	
Supports incumbent	0.48	0.56	0.09	0.50	0.47	0.23
	(0.50)	(0.50)		(0.50)	(0.50)	
Voted in previous election	0.76	0.70	0.06	0.74	0.78	0.88
	(0.43)	(0.46)		(0.44)	(0.41)	
Knows public pharmacy	0.67	0.60	0.04	0.64	0.69	0.08
	(0.47)	(0.49)		(0.48)	(0.46)	
Perceived relative price of public pharmacy	0.46	0.47	0.54	0.46	0.46	0.55
	(0.23)	(0.18)		(0.18)	(0.26)	
Perceived days to delivery at private pharmacy	8.52	8.53	1.00	9.71	7.67	0.80
	(12.00)	(12.73)		(14.74)	(9.49)	
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 ($\hat{P}_{X}$)	
Public pharmacy 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)	
	[0.007]		[0.006]		[0.004]		[0.001]		[0.003]		[0.000]	
Public pharmacy 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)
		[0.008]		[0.005]		[0.004]		[0.001]		[0.005]		[0.000]
Public pharmacy 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)
		[0.007]		[0.007]		[0.005]		[0.002]		[0.003]		[0.000]
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 (5). 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. We also provide standard errors clustered at the location level, and are displayed in square brackets.

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 public pharmacy	-0.039***	-0.041***		0.006**	0.009***	
	(0.011)	(0.005)		(0.003)	(0.001)	
	[0.013]	[0.013]		[0.004]	[0.004]	
First public pharmacy × chronic (β_C)			-0.054***			0.009***
			(0.006)			(0.001)
			[0.014]			[0.004]
First public pharmacy × non-chronic (β_{NC})			-0.023***			0.010***
			(0.008)			(0.002)
			[0.013]			[0.005]
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. We also provide standard errors clustered at the location level, and are displayed in square brackets.