Pharmacy Access and Health-seeking Behavior: Evidence from a Nationwide Policy*

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Abstract

Developing countries have wide geographical differences in access to healthcare services. While programs that aim to improve hospital-supporting institutions might improve access for large swaths of the population that cannot access healthcare, they might have an unintended consequence of substitution away from hospitals or clinics to relying on pharmacies for healthcare. Furthermore, unregulated dispensation of medicines may lead to increased incidence of antibiotic resistance in the population who rely on these pharmacies, bypassing healthcare at a hospital or clinic. In this paper, I study a nationwide program in India that improved access to pharmacies by providing cheap generic medicines. Using a difference-in-differences framework relying on geographic variation in access to these pharmacies, I find that exposed respondents are more likely to report receiving some treatment for acute ailments. This increase in healthcare-seeking behavior, however, leads to a shift away from treatment at a hospital or clinic to treatment at a pharmacy. I also find that economically and socially disadvantaged subgroups are more likely to report this substitution pattern, pointing to worsening inequality in access to quality healthcare. I reflect on potential mechanisms driving the main effect and find evidence for finance as a likely mechanism for the observed healthcare-seeking behavior in the exposed population. My main conclusions are robust to a host of empirical checks.

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1 Introduction

Antimicrobial resistance (AMR) is an emerging health issue. In 2015, WHO adopted a global action plan to counter the increasing incidence of AMR across the globe (WHO, 2015). In low- and middle-income countries (LMIC), AMR is steadily becoming a public health issue. Due to weak regulation on top of almost nonexistent enforcement of antibiotic dispensation rules, pharmacists and customers are incentivized to rely on self-medication often in the form of indiscriminate antibiotic consumption even for non-bacterial infections like viral fevers. It is expected that AMR may lead to a cumulative loss of 100 trillion USD if steps are not taken to rein in the incessant consumption of antibiotics, often without merit (World Bank, 2017).

The canonical models of health demand predict that conditional on quality, the health demand increases when its price decreases (Grossman, 1972, 2000). If the agents perceive the quality of healthcare received at the pharmacy and hospital is similar, then better access to pharmacies might induce a shift away from institutional care. This substitution pattern might be more pronounced for those who cannot afford the cost of doctors' consultations and medicines. In LMIC where healthcare providers are overstretched, there might be increased impetus to altogether bypass institutional care. Despite these predictions, there is a lacuna in our understanding of how improved access to pharmacies affects provider choices, especially within the context of an LMIC. In this paper, I aim to fill this gap.

To uncover the effects of healthcare seeking behavior due to improved access to pharmacies, I leverage a nationwide program in India–*Pradhan Mantri Bhartiya Janaushadhi Pariyojana (PMBJP)*. This program provides high-quality generic medicines along with incentivizing entry through higher sales margins and grants to establish pharmacies. Although the policy is aimed to be national in its geographic reach, many sub-districts (third tier of administrative division in India) did not have access to these pharmacies even in December 2023.[1] Although not all drugs sold by the pharmacies in India can be obtained without a prescription, weak regulatory oversight means that dispensation is hardly curtailed due to fear of financial or legal repercussions of rule violations (Laxminarayan and Chaudhury, 2016; Porter et al., 2021). Therefore, conceivably sub-districts that have access to these pharmacies provide a relatively cheaper substitute for healthcare than a doctor or clinician visit.

I rely on multiple rounds of Demographic and Health Surveys (DHS) to examine if access to *PMBJP* pharmacies changes healthcare seeking behavior. The first of these survey rounds was fielded in 2015-16 and the later one in 2019-21 with a gap of one year due to the COVID-19 pandemic. DHS provides detailed information on the health outcomes for women aged 15 to 49 in the surveyed households. These data also allow me to obtain detailed information on the health outcomes for the youngest child born within five years preceding the survey date. In particular, I know if an antibiotic is prescribed or consumed

[1] This conclusion is drawn from the directory of *PMBJP* pharmacies that are operational during this month.

as part of treatment for an acute ailment for this child. Information on *PMBJP* pharmacies was obtained from the administrative data provided by the implementing agency and scraped in late 2023. Using the geolocation of DHS clusters accounting for random displacement, I classify the residence sub-district to have a *PMBJP* pharmacy if it has at least one such establishment.

As I lack precise information on which *PMBJP* began operation, I classify all respondents from the 2015-16 survey round to not be exposed to the policy. The validity of this assumption is justified through anecdotal evidence of poor functioning of the pharmacies during this period with frequent product recall and stock shortages. I employ a difference-in-differences (DID) framework to provide a causal estimate of the intention-to-treat (ITT) effect of *PMBJP* pharmacy access. By accounting for level differences across sub-districts and secular changes in the outcome variables, my research design provides a consistent estimate of access to cheap drugs on healthcare seeking behavior. I establish the robustness of my empirical approach through a series of robustness checks including allowing for states to trend differentially.

My main results indicate that relative to residents of sub-districts that do not have a *PMBJP* pharmacy, respondents with access to these pharmacies are more likely to report having some treatment in the 2019-2021 round of DHS when compared to the 2015-16 round. The increase is quantitatively meaningful at approximately 9% of the 2015-16 mean for sub-districts that have the pharmacies. Additionally, this increase in overall treatment likelihood comprises a large increase in the likelihood of receiving treatment at a pharmacy along with the decrease in treatment at a hospital or clinic, albeit the latter is not statistically significant at conventional levels of statistical significance. I also establish that the substitution from hospital or clinic treatment to pharmacy is one-to-one. While being positive, the likelihood of antibiotic consumption is not statistically significant at conventional levels of statistical significance.

My heterogeneity analysis reveals a gender asymmetry in the likelihood of treatment at a hospital or clinic post-pharmacy entry. While males increase, females reduce treatment at a hospital or clinic after their residence sub-district gets a *PMBJP* pharmacy. Having access to health insurance prevents the substitution between hospital or clinic and pharmacy treatment. As health insurance access is often tied to work, the substitution pattern is observed for only those respondents who have weak labor market attachment. I do not find differences in substitution between hospital or clinic and pharmacy treatment across other socioeconomic characteristics, including wealth, of the respondents. Overall, the existing inequities in healthcare access might be accentuated due to *PMBJP* pharmacy entry.

DHS data does not allow me to undertake extensive mechanism analysis. Nonetheless, I provide evidence for financial constraints potentially driving the changes in healthcare behavior. I find that respondents are less likely to report not using contraceptives or family planning methods due to cost or transport reasons after their residence sub-district experiences a *PMBJP* pharmacy entry. Lending further credence to this conclusion, I also document a decline in the index of financial and transportation reasons for not seeking

healthcare post-policy.

This paper contributes multiple strands of existing literature. By highlighting unintended consequences in terms of substitution between hospital or clinic and pharmacy care, I add to a nascent literature on the health effects of improving access to pharmacies in developing countries (Atal et al., 2024). Highlighting the role of pharmacy access in widening the existing socioeconomic inequities in healthcare, I add to the literature studying myriad drivers of these inequities (Wagstaff and van Doorslaer, 2000). This paper is also related to the literature on the effects on the local market due to the entry of stores (Bennett and Yin, 2019; Frank and Salkever, 1997; Moura and Barros, 2020). Finally, I examine the role of a contextual feature that may engender the preferences for health demand (Grossman, 1972, 2000).

The rest of the paper proceeds as follows. I provide a brief background in Section 2. Section 3 provides details on the data employed. Empirical strategy is discussed in Section 4. All results are reported in Section 5. Section 6 concludes.

2 Background

Pradhan Mantri Bhartiya Janaushadhi Pariyojana (PMBJP) is a national welfare scheme in India. The scheme aims to provide high-quality generic medicine at a reduced price. The Department of Pharmaceuticals manages it under the central government's Ministry of Chemicals and Fertilizers. The scheme operates through various pharmacies across the country. These pharmacies are called *Janaushadhi Kendra*.

Under the scheme, pharmacies (hereafter *PMBJP* pharmacies) sell drugs and surgical items. In my data, more than 10,000 pharmacies are operational through the scheme. The central government procures the medicines through tenders, and they are distributed to the pharmacies operating under the scheme. Consumers can obtain Over-the-counter (OTC) drugs without a prescription, while "schedule" drugs require a prescription from a registered medical practitioner.

Almost all individuals and institutional entities, including local governments, can apply for a pharmacy license. A retail drug license is required to apply to operate a pharmacy under the scheme successfully. In addition to this requirement, the applicant must demonstrate that they can hire a pharmacist with at least an undergraduate pharmacy degree.

The scheme provides significant financial incentives to operate and open a pharmacy. A 20% margin between the price paid at the procurement of medicine and the price paid by the end consumer for each drug is provided. This is much higher than the typical 16% margin for other retailers. A one-time grant totaling two *lakh* rupees ($\sim$\$2400) is provided to applicants meeting specific criteria. The scheme also provides monetary incentives for all medicines that are procured from the Pharmaceuticals & Medical Devices

Bureau of India (PMBI). PMBI is responsible for the scheme's procurement, supply, and marketing of generic drugs.

While the scheme started in 2008, there has been increased impetus to widen its reach since 2016-17. Furthermore, there were multiple product recalls and stock shortages till 2018 (Chandna, 2021). I am unable to obtain information on the sub-districts that have operational *PMBJP* pharmacies for this period. This suggests that even if a sub-district has a *PMBJP* pharmacy, it is unlikely to be widely used (Pareek and Prakash, 2019). Therefore, I assign all sub-districts to have no *PMBJP* pharmacy for the fourth round of NFHS conducted in 2015 and 2016.

3 Data

The ideal data to examine how access to pharmacies affects health-seeking behavior and health outcomes would contain information on these outcomes along with information on access to pharmacies. Additionally, the study of potential mechanisms driving the observed effects would be aided by information on reasons driving individual behavior as regards their healthcare choices. While I cannot access such detailed data, I combine multiple sources to approximate these ideal data. In this section, I detail each data source that I employ to examine the health effects of improved access to pharmacies.

3.1 Data on Healthcare Choices and Health Outcomes

I use nationally representative data on healthcare choices and health outcomes from two rounds of the National Family Health Survey (NFHS). These rounds are conducted in 2015-16 and 2019-2021, respectively. These data survey respondents from all districts in the country.

NFHS follows a two-stage sampling design. For rural areas, villages are primary sampling units (PSUs) with the probability of selection proportional to their population. Census Enumeration Blocks (CEB) constitute PSUs for urban areas in the first-stage.[2] At the second-stage in both rural and urban areas, 22 households are randomly selected from each PSU. Household selection in the second-stage proceeds after complete mapping and household listing in the selected first-stage units.

NFHS collects detailed information on the health-seeking behavior of the respondents. For adult members of the surveyed households, the survey collects information if the respondent visited a health facility or camp for any reason, either for themselves or for their children.[3] Information on the facility or camp

[2]Each CEB in an urban area contains around 125 households or approximately 625 individuals. CEBs are the smallest aggregate unit in India's Population and Housing Census.

[3]The specific question for adults in the survey is "In the last three months, have you visited a health facility or camp for

type is also collected for adults who visited any health facility or camp. I observe whether the respondent reported using the pharmacy as the facility for their healthcare visit. I classify all respondents as having received treatment at the pharmacy if they report it as their choice of health facility.

More detailed information on health-seeking behavior and health outcomes of children under five at the time of the survey is also available in NFHS.[4] In addition to the information discussed above for adult members in the household, NFHS also provides information on the prescribed medicines for all children aged five years or younger.[5] This information is available for all children who received diarrhea, fever, or cough treatment. I specifically use information on whether any antibiotic is prescribed for these ailments on account of having received treatment for them.

In order to tease out potential mechanisms through which improved access to pharmacies may affect health-seeking behavior and health outcomes, I also use information on pregnancy complications for female respondents. I observe whether financial or transportation constraints are the reasons for respondents who do not seek treatment for pregnancy complications.

To test if improved information about available healthcare services is a channel leading to estimated effects, I also use the information on whether the adult respondent reports pharmacy as the place where family planning methods can be obtained. I also observe in NFHS if the respondent reported purchasing condoms or where advice or treatment was obtained for sexually transmitted diseases from pharmacies. Trust in the healthcare provider might be a channel through which respondents increasingly rely on pharmacists to obtain medicines for acute care. An increased likelihood of reporting condoms from the pharmacy might suggest elevated trust between the respondent and the pharmacist.

In order to assign respondents as having access to a *PMBJP* pharmacy or not, I rely on NFHS cluster locations. NFHS clusters are randomly displaced in order to protect respondent identity. Urban clusters are displaced up to two kilometers. Rural clusters are displaced up to five kilometers, with one percent of the clusters displaced up to ten kilometers.

Using sub-district shapefiles obtained from Asher et al. (2021), I assign an urban cluster to a sub-district if the two-kilometer buffer around the cluster location lies completely within that sub-district. A rural cluster is assigned a sub-district if the ten-kilometer buffer around the cluster location completely lies within that sub-district. I take a five-kilometer buffer around the cluster location for the remaining rural clusters and assign it to the sub-district if it lies completely within that sub-district. In a robustness check

any reason for yourself (or for your children)?".

[4]For all children under five, the survey asks the following questions: (1) "Did you seek advice or treatment for diarrhea from any source?" (2) "Did you seek advice or treatment for the illness (fever or cough) from any source?" It should be noted that the recall period for health-seeking behavior for children is two weeks. If the respondent responds to these two questions affirmatively, they are asked the place where the treatment was sought. I highlight that, unlike adults, the survey allows children to seek treatment at multiple sources. In a robustness check later, I show that restricting the analytical sample to only adults does not alter my findings.

[5]The survey asks the type of drugs taken as part of treatment. The specific question is "What drugs did the child take?"

later, I randomly and multiple times drop one percent of the rural clusters with a five-kilometer buffer that could be assigned a sub-district to ensure that my results are not conflated by misclassification of rural clusters to sub-districts (see Figure A2).

3.2 Data on *PMBJP* Pharmacies

Data on *PMBJP* pharmacy locations comes from the Department of Pharmaceuticals, Ministry of Chemicals & Fertilizers, Government of India.[6] These data provide information on unique pharmacy identifiers, the district in which the pharmacy is located, the pharmacy's address, the name of the contact person, and the status of the pharmacy.

In order to assign sub-districts to each pharmacy, I rely on `Bing Maps API`.[7] Using the full address and pin code of the pharmacy, I am able to obtain the location of each pharmacy. This location information is then projected on the sub-district shapefiles obtained from Asher et al. (2021). Therefore, I am able to assign a sub-district to each pharmacy in my sample. Hereafter, all sub-districts with at least one *PMBJP* pharmacy are referred to as treated sub-districts, while those without these pharmacies are referred to as control sub-districts. Figure 1 shows sub-districts with at least one *PMBJP* and those without. This figure suggests substantial spatial variation in *PMBJP* pharmacy availability across sub-districts.

Sub-districts with a *PMBJP* pharmacy and those without are potentially different in their observable characteristics. To account for differences in these observable characteristics, I reweigh all sub-districts that do not have a *PMBJP* pharmacy. Using Probit estimation, I predict the likelihood of a sub-district having a *PMBJP* pharmacy. I use population variables as predictors in this estimation. Predicted probabilities from Probit estimation are used as weights. Estimates from this estimation are presented in Table A1.

3.3 Descriptive Statistics

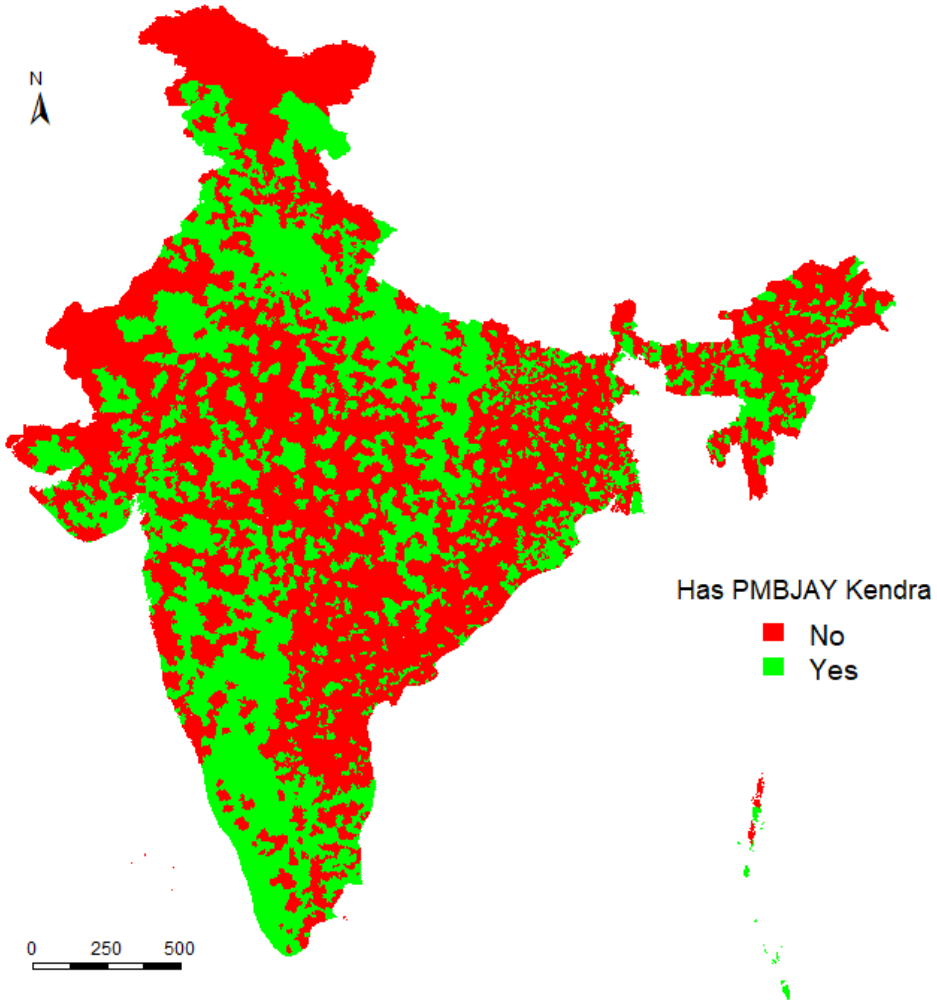
Table A2 presents descriptive statistics. Panel A presents the mean of sub-district characteristics. Sub-districts that do not have any *PMBJP* pharmacy are smaller in size. After reweighting these sub-districts, the population means are comparable to sub-districts having access to *PMBJP* pharmacies.

Panel B of Table A2 presents the mean for outcome variables. Respondents in sub-districts with at least one *PMBJP* pharmacy seek treatment at a higher rate. These respondents are also prescribed antibiotics at a higher rate than their counterparts in a non-*PMBJP* pharmacy sub-district.

[6] I obtained data on *PMBJP* pharmacies at https://janaushadhi.gov.in/KendraDetails.aspx. The link was accessed in December 2023.

[7] More information on this API can be accessed at https://www.microsoft.com/en-us/maps/bing-maps/choose-your-bing-maps-api.

Figure 1: Sub-District *Pradhan Mantri Bhartiya Janaushadhi Pariyojana (PMBJP)* Pharmacy Access



Note: The sub-district polygons come from the 2011 Census of India (Asher et al., 2021). A sub-district polygon is filled with the color green if that sub-district has one or more *PMBJP* pharmacies. A sub-district without any *PMBJP* pharmacy has a red color-filled polygon.

Panel C presents the mean for individual characteristics. I emphasize that respondents in sub-districts without a *PMBJP* pharmacy are relatively poorer and less educated than respondents in a sub-district with at least one *PMBJP* pharmacy. While presenting results, I examine if the estimated effects differ across these individual characteristics.

4 Empirical Strategy

I study the effect of having access to *PMBJP* pharmacy on health-seeking behavior and health outcomes. In this section, I discuss the empirical model that I estimate. I also discuss potential threats to the identification of causal effects. I detail how I address these concerns.

My main empirical is presented in Equation 1.

$$(1) \quad y_i = \alpha_{i(sd)} + \alpha_{i(m\times y)} + \beta \cdot \left[\mathbb{1}\left(\text{Any } \textit{PMBJP} \text{ Pharmacy}\right)_{i(sd)} \times \mathbb{1}\left(\text{NFHS Round 5}\right)_i\right] + \mathbf{X}_i\gamma + \varepsilon_i$$

In Equation 1, y_i is the outcome variable for respondent i. I examine four main outcomes. The first outcome variable is an indicator for whether the respondent seeks any treatment. The second and third outcome variables are indicators for whether the treatment is received at the pharmacy or at the hospital/clinic. The final outcome variable is an indicator for whether an antibiotic is prescribed during the treatment or not.

$\alpha_{i(sd)}$ and $\alpha_{i(m\times y)}$ are sub-district and month-times-year-of-survey fixed-effects. Sub-district fixed-effects control for time-invariant observable and unobservable sub-district characteristics that are correlated with both having access to *PMBJP* pharmacies and health-seeking behavior or health outcomes. Geographical conditions like terrain and ruggedness are examples of such sub-district unobservables. Time fixed-effects control for time-varying secular shocks such as the spread of diseases or infection in the population.

Equation 1 also controls for individual characteristics that may affect treatment exposure and outcomes of interest. These individual characteristics are represented by vector $\mathbf{X}_i$. The vector of individual characteristics contains an indicator for the sex of the respondent, indicators for the religion of the respondent, and the age of the respondent. ε_i is an idiosyncratic error term which I cluster at the sub-district level (Abadie et al., 2022).

The parameter of interest in Equation 1 is β. β is the marginal effect of having any *PMBJP* pharmacy in the sub-district in the fifth round of NFHS relative to round four on the outcome variable. $\mathbb{1}\left(\text{Any } \textit{PMBJP} \text{ Pharmacy}\right)_{i(sd)}$ is an indicator that takes a value one if sub-district sd where respondent i resides has any *PMBJP* pharmacy and zero otherwise. $\mathbb{1}\left(\text{NFHS Round 5}\right)_i$ is an indicator that turns on if respondent i is interviewed in the fifth round of NFHS and zero if they are interviewed in round four. The interaction of these two variables is referred to as the access variable hereafter.

In order to interpret β as the causal effect of having access to *PMBJP* pharmacy on the health-seeking behavior and health outcomes, it must be true that unobservables correlated with the outcome variable are uncorrelated with the access variable, conditional on various fixed-effects and individual-level controls. This is akin to the parallel trends assumption in the difference-in-differences (DID) empirical framework.

One way to address the potential violation of this assumption is to reweight the sub-districts without a *PMBJP* pharmacy so that they are comparable along the observable characteristics to sub-districts with such pharmacies. As shown in Table A2, the unweighted population means are different between treated and control sub-districts. Upon reweighing, control and treated sub-districts are much more comparable in their population means.

As discussed in Section 2, I do not have access to information on when the pharmacy became operational. This implies that I may be misclassifying sub-districts that do not have any *PMBJP* pharmacy during the fifth survey round of NFHS as having access to these pharmacies. It is very unlikely that once a pharmacy becomes operational, it will close down in the near future. This is also borne out in the scheme's annual reports. These annual reports suggest that there has been a steady increase in the number of pharmacies over the years.[8]

Recent work establishes that in the presence of unidirectional misclassification in DID settings without false negatives, the estimated effect is attenuation of the true average treatment effect on the treated (ATT) (Denteh and Kédagni, 2022). Given this and the very unlikely closure of operational pharmacies, my estimated effects can be interpreted as lower bounds on the true effects of having access to a *PMBJP* pharmacy on health-seeking behavior and health outcomes.

I also attempt to assuage concerns related to unobservable shifts that differ across treatment and control groups between two rounds of NFHS. Two NFHS rounds that I can access do not lend themselves well to a canonical event-study framework. This is due to a significant gap between the timing of the two survey rounds. Nonetheless, I present estimates from the following event-study framework.

$$
\begin{aligned}
(2) \quad y_i = {} & \alpha_{i(sd)} + \alpha_{i(m\times y)} + \sum_{j=-8}^{-1} \beta_j \cdot \left[\mathbb{1}\left(\text{Any } \textit{PMBJP} \text{ Pharmacy}\right)_{i(sd)} \times \mathbb{1}\left(\text{Quarter to Treatment} = j\right)_i \right] \\
& + \sum_{j=9}^{17} \beta_j \cdot \left[\mathbb{1}\left(\text{Any } \textit{PMBJP} \text{ Pharmacy}\right)_{i(sd)} \times \mathbb{1}\left(\text{Quarter to Treatment} = j\right)_i \right] \\
& + \mathbf{X}_i\gamma + \varepsilon_i
\end{aligned}
$$

The specification in Equation 2 is similar to the specification in Equation 1, except that a single indicator variable for respondent i to be interviewed in the fifth round of NFHS, $\mathbb{1}\left(\text{NFHS Round 5}\right)_i$, is replaced with a set of indicators for quarter relative to treatment, $\mathbb{1}\left(\text{Time to Treatment} = j\right)_i$.

The quarter relative to the treatment is measured in quarters of the calendar year. Specifically, I treat the first quarter after the latest quarter in which a respondent is interviewed in the fourth round of NFHS as the first quarter post-treatment. The first quarter during which any interview is conducted in the fifth

[8] See page 42 of the 2021-22 annual report at https://janaushadhi.gov.in/Data/Annual%20Report%202021-22_04052022.pdf.

round of NFHS is nine quarters after the last quarter of the interview in the fourth round. Therefore, the post-treatment set of quarters relative to treatment indicators ranges from nine to seventeen in Equation 2.

Figure A1 presents results from the estimation of specification in Equation 2. I present estimates for all four main outcome variables. These estimates suggest that there is no evidence of pre-trends in the outcome variables except for the outcome variable related to antibiotic prescription. Consequently, I exercise caution in interpreting the estimates from specifications where the outcome variable is antibiotic prescription during treatment.

I also estimate a specification where the treatment is assumed to be multivalued. The specification that I estimate is presented in Equation.

$$y_i = \alpha_{i(sd)} + \alpha_{i(m\times y)} + \beta \cdot (\#\ PMBJP \text{ Pharmacies}) + \mathbf{X}_i\gamma + \varepsilon_i \tag{3}$$

Equation 3 is similar to Equation 1, except that the indicator for whether the sub-district has any *PMBJP* pharmacy or not is replaced with the count of such pharmacies. For responses from the fourth round of NFHS, the count is assumed to be zero for all sub-districts.

Recent work suggests that under parallel trends assumptions, a causal estimate of parameter β can be obtained (Callaway et al., 2024). Implementation of this estimation strategy, however, requires panel data. I, therefore, aggregate individual observations up to sub-districts. The following specification is estimated using these aggregated data.

$$\Delta y_i = \beta_0 + \sum_{j=1}^{J} 1\left\{(\#\ PMBJP \text{ Pharmacies})_i = j\right\} \cdot \beta_j + \varepsilon_i \tag{4}$$

In Equation 3, β_j is the ATT where the treatment is having j *PMBJP* pharmacies.

5 Results

In this section, I present the main results on health-seeking behavior in the sub-districts that have *PMBJP* pharmacies. I establish the robustness of my main estimates to various empirical checks. Then, I examine if the main effects vary across subpopulations. Finally, I shed light on potential mechanisms that may be leading to the main effects.

5.1 Main Results

I start by presenting estimates from Equation 1 in the top panel of Table 1. The first column presents estimates from the specification where the outcome variable is an indicator variable for whether the respondent reports receiving any treatment at a health facility or camp for themselves or for any member of the household. The point estimates show that having a *PMBJP* in the residence sub-district increases the likelihood of receiving treatment. The point estimate corresponds to an approximate increase in the treatment likelihood of 2.96 percentage points, a 8.55% increase over the pre-treatment mean for the sub-district that has access to *PMBJP* pharmacies.

Does having access to a pharmacy selling reduced-price medicines reduce healthcare seeking in hospitals or clinics? I provide evidence for almost one-to-one substitution between pharmacy and hospital or clinic in sub-districts that experience *PMBJP* pharmacy entry. The point estimate for the specification with the dependent variable as an indicator for whether the respondent reports receiving treatment at a pharmacy is positive and highly statistically significant. After the sub-district has at least one *PMBJP* pharmacy when compared to a sub-district without *PMBJP* pharmacy the likelihood of receiving treatment at the pharmacy increases by approximately 1 percentage point relative to the period before the *PMBJP* pharmacy entry. This is almost a 36% increase over the pre-treatment mean for the sub-districts that eventually have a *PMBJP* pharmacy entry.

At the same time, residents of sub-districts with *PMBJP* pharmacies reduce healthcare seeking in hospitals or clinics. This effect, however, is not statistically significant at the conventional levels of significance. Taken together, the point estimates in column (2) and column (3) are extremely close and I cannot reject the null hypothesis that there is one-to-one substitution between pharmacies and hospitals or clinics (p-value > 0.10).

In the last column of Table 1, I report estimates from the specification where the dependent variable is an indicator for whether the respondent used antibiotics as part of their treatment. I note that this variable is defined only for children who are five years or younger at the time of the survey. Furthermore, as was noted above Figure A1 shows that the identifying assumption of parallel trends for the estimates from Equation 1 to be interpreted causally is not satisfied for this variable. Therefore, I do not emphasize the estimates for this outcome variable. Nonetheless, the point estimate suggests that access to *PMBJP* pharmacy in the sub-district is positively associated with an increase in the likelihood of reporting antibiotic consumption as part of treatment.

On the intensive margin, each additional *PMBJP* pharmacy in the sub-district leads to no change in the likelihood of overall healthcare-seeking behavior of the residents. The substitution between treatment at a pharmacy and hospital or clinic is still observed when the *PMBJP* pharmacies become more widespread (p-value > 0.10).

Table 1: Access to Pharmacy and Health Outcomes: Main Estimate

	Any Treatment (1)	Treatment at Pharmacy (2)	Treatment at Hospital/Clinic (3)	Antibiotic Taken (4)
Panel A: Any *PMBJP* Pharmacy				
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0296***	0.0099***	-0.0105	0.0336
	(0.0090)	(0.0026)	(0.0126)	(0.0269)
Adj. R2	0.075	0.021	0.213	0.060
Dep. Var. Mean	0.293	0.020	0.768	0.247
N	733,782	220,941	220,941	27,922
Panel B: Number of *PMBJP* Pharmacy in the Sub-District				
# *PMBJP* Pharmacies	0.0004	0.0002***	-0.0001	0.0009
	(0.0003)	(0.0001)	(0.0002)	(0.0008)
Adj. R2	0.075	0.021	0.213	0.060
Dep. Var. Mean	0.293	0.020	0.768	0.247
N	733,782	220,941	220,941	27,922

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each cell in Panel A is a separate estimation of specification in Equation 1. The estimate in each cell in Panel A is for the interaction of an indicator variable for whether the sub-district has any *PMBJP* pharmacy and an indicator variable for the respondent to have been surveyed in the fifth round of the National Family Health Survey (NFHS). Each cell in Panel B is a separate estimation of specification in Equation 3. The estimate in each cell in Panel B is for the count of *PMBJP* pharmacies in the sub-district. All sub-districts in the fourth round of NFHS are assumed to have no *PMBJP* pharmacy. Each specification also includes control variables for respondents' age, an indicator for the respondent to be male, and indicators for the respondent to be following Hinduism and Islam. In Panel A, all sub-districts that have at least one *PMBJP* pharmacy comprise the treatment group. The Independent variable in Panel A is an indicator variable for a sub-district having any *PMBJP* pharmacy. In Panel B, the independent variable is the count of *PMBJP* pharmacies. The dependent variable is in the column header. In column (1), the dependent variable is an indicator variable for whether the respondent visits a health facility or camp for any reason for themselves or for any member of the household. In column (2), the dependent variable is an indicator variable for whether the respondent reports visiting the pharmacy for treatment. In column (3), the dependent variable is an indicator for whether the respondent reports visiting a hospital or clinic for treatment. The dependent variable in column (2) and column (3) is defined only if the respondent reports visiting a health facility or camp for any reason for themselves or for any member of the household. In column (4), the dependent variable is an indicator variable for whether the respondent reports taking antibiotics for the ailment. The sample in column (4) is restricted to children under the age of five and if they seek treatment for diarrhea, fever, or cough. Data on outcome variables and controls are derived from the fourth and fifth rounds of NFHS. Data on *PMBJP* pharmacy locations comes from the Department of Pharmaceuticals, Ministry of Chemicals & Fertilizers, Government of India.

Overall, results in Table 1 paint a picture of an increase in healthcare-seeking behavior of respondents when their residence district receives a *PMBJP* pharmacy. *PMBJP* pharmacy access, however, leads to an almost one-to-one substitution between treatment at a pharmacy and treatment at a hospital or clinic. Next, I establish the robustness of this conclusion to various empirical checks.

5.2 Robustness Checks

Table A3 and Table A4 present various robustness checks for the extensive and intensive margin of treatment, respectively. The first panel in both tables reports estimates from Table 1. The second panel drops children who are under the age of five years at the time of the survey from the estimating sample. The third panel of the table adds control for the number of pharmacies in the sub-district to the specification in Equation 1 and 3. Data on the number of pharmacies in the sub-district is derived from the Population and Housing Census 2011. The fourth panel (Panel D) clusters standard errors at the district-level. Point estimates in these four panels are extremely close to each other and I cannot reject the null hypothesis that they are equivalent for all four outcome variables. This suggests that conclusions drawn from estimates in Table 1 are unaltered when I change the estimation sample, account for existing access to pharmacies in the sub-district, or cluster standard errors at relatively more coarse geography.

I control for state linear time trends in the last column (Panel E) of Table A3 and A4. The inclusion of these linear time trends allows the outcomes to trend differentially across states, albeit only linearly. As healthcare is a state subject where states are allowed to change the healthcare landscape in the state, state linear time trends explicitly account for this. However, the precision of estimates is worsened when I include state linear time trends as the identifying variation is derived from changes away from the state linear time trends. This is borne out by the imprecise point estimates reported in the last panel of Table A3 and Table A4.

Recall that one percent of the rural DHS clusters are displaced by up to 10 kilometers. To ensure that my point estimates are not conflated by the misclassification of rural clusters to the sub-district, I randomly drop one percent of the rural clusters in my estimation sample and repeat this randomization process 500 times. I present the density of point estimates for all four outcome variables from this procedure in Figure A2. The main point estimates in Table 1 are centered approximately around the median of the distribution of point estimates from the randomization procedure. This suggests that the misclassification of rural clusters that are displaced up to 10 kilometers does not drive my main effect.

Taken together results in this subsection show that an increase in overall healthcare-seeking behavior and one-to-one substitution between the treatment at a pharmacy and treatment at a hospital or clinic when the respondents' residence sub-district receives a *PMBJP* pharmacy is robust to multiple sensitivity checks. In the following subsection, I examine if the main effect varies across subpopulations.

5.3 Heterogeneity

In this subsection, I investigate if the main effects differ across subpopulations. In particular, I examine if there is a difference in how subpopulations with different demographic characteristics, wealth, and

residing in different geographies respond to a *PMBJP* pharmacy entry in their residence sub-district.

Table 2 presents estimates from estimating specification in Equation 1 for respondents with different sex and ages. In the first two columns, I present estimates for all four outcome variables by respondents' sex. I observe that there is no statistically significant difference in the extent to which overall healthcare-seeking behavior increases for both the sex (p-value: 0.69). While the point estimates for whether the treatment is received at a pharmacy is positive for both male and female respondents, it is only statistically significant for females. Furthermore, I am unable to reject the null hypothesis that the point estimate for both sexes is the same for treatment at the pharmacy (p-value: 0.50). Albeit statistically insignificant, male and female respondents respond differently to a *PMBJP* pharmacy entry in their residence sub-district concerning treatment at a hospital or clinic, with females reducing and males increasing treatment at these institutions. Indeed, it is the case that this differential response is statistically significant (p-value: 0.04).

Receiving healthcare in a hospital or clinic in India is expensive. It is also the case that pharmacists are unable to treat or diagnose ailments at a level that a health personnel in a hospital or clinic can do. This amounts to a low quality of healthcare for treatment at a pharmacy. Given the systemic negligence of female members of households in terms of quality of care received relative to male members (Saikia et al., 2016), reduction of treatment in hospital or clinic for female respondents suggests that *PMBJP* pharmacy entry in the sub-district might be widening the existing intrahousehold gender inequality in quality of healthcare received.

I do not find that antibiotic consumption as part of treatment differs across male and female children (p-value: 0.14). Moreover, neither boys nor girls see a statistically significant change in their antibiotic consumption when their residence sub-district is afforded a *PMBJP* pharmacy.

Next, I study if the main effects vary across age categories. The estimates from the specification in Equation 1 for distinct age categories are presented in column (3) to column (5) of Table 2. I classify respondents into three mutually exclusive and exhaustive age categories. The first age category is all children who are five years of age or younger. The second age category consists of all respondents who are between the ages of 15 and 30 years. The final category is for all the respondents who are 30 years of age or older. For children below five years of age, entry of a *PMBJP* leads to an increase in overall healthcare-seeking behavior and this effect is statistically significant at a 10 percent significance level. I find no change in overall treatment likelihood for middle-aged respondents (age 15 to 30) and I cannot reject the null hypothesis that the effect for these respondents differs statistically significantly from younger respondents (age five or younger) (p-value: 0.50).

The older respondents, however, report a higher likelihood of seeking healthcare for any reason for themselves or any other member of the household. Specifically, older respondents (age 30 or more) are five percentage points more likely to report having sought any treatment in the month preceding the date

Table 2: Heterogeneity: Sex and Age

	Sex		Age		
	Male	Female	Age ≤ 4	$15 \leq$ Age ≤ 30	Age > 30
	(1)	(2)	(3)	(4)	(5)
Panel A: Any Treatment					
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0350***	0.0300***	0.0157*	0.0061	0.0528***
	(0.0105)	(0.0103)	(0.0091)	(0.0104)	(0.0162)
Adj. R2	0.079	0.077	0.091	0.108	0.092
Dep. Var. Mean	0.213	0.315	0.146	0.337	0.328
N	157,319	576,392	154,774	310,343	268,651
Panel B: Treatment at Pharmacy					
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0056	0.0101***	0.0158**	0.0134***	0.0069*
	(0.0062)	(0.0027)	(0.0080)	(0.0038)	(0.0041)
Adj. R2	0.018	0.018	-0.015	0.020	0.018
Dep. Var. Mean	0.031	0.017	0.045	0.016	0.016
N	36,094	184,484	27,922	104,537	87,830
Panel C: Treatment at Hospital/Clinic					
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0196	-0.0206	0.0288	-0.0227*	-0.0203
	(0.0171)	(0.0131)	(0.0211)	(0.0124)	(0.0195)
Adj. R2	0.437	0.065	0.037	0.334	0.529
Dep. Var. Mean	0.295	0.861	0.709	0.776	0.780
N	36,094	184,484	27,922	104,537	87,830
Panel D: Antibiotic Taken					
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0271	-0.0211	0.0336		
	(0.0257)	(0.0287)	(0.0269)		
Adj. R2	0.027	0.064	0.060		
Dep. Var. Mean	0.248	0.248	0.247		
N	14,570	12,584	27,922		

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each cell is a separate estimation of specification in Equation 1. Each specification also includes control variables for respondents' age, an indicator for the respondent to be male, and indicators for the respondent to be following Hinduism and Islam. The estimate in each cell is for the interaction of an indicator variable for whether the sub-district has any *PMBJP* pharmacy and an indicator variable for the respondent to have been surveyed in the fifth round of the National Family Health Survey (NFHS). All sub-districts that have at least one *PMBJP* pharmacy comprise the treatment group. The Independent variable in Panel A is an indicator variable for a sub-district having any *PMBJP* pharmacy. In Panel B, the independent variable is the count of *PMBJP* pharmacies. The dependent variable is in the column header. In Panel A, the dependent variable is an indicator variable for whether the respondent visits a health facility or camp for any reason for themselves or for any member of the household. In Panel B, the dependent variable is an indicator variable for whether the respondent reports visiting the pharmacy for treatment. In Panel C, the dependent variable is an indicator of whether the respondent reports visiting a hospital or clinic for treatment. The dependent variable in Panel B and Panel C is defined only if the respondent reports visiting a health facility or camp for any reason for themselves or for any member of the household. In Panel D, the dependent variable is an indicator variable for whether the respondent reports taking antibiotics for the ailment. The sample in Panel D is restricted to children under the age of five and if they seek treatment for diarrhea, fever, or cough. Column headers denote the subpopulation that comprises the analytical sample. All subpopulations are from the self-reported responses in the survey data. Data on outcome variables and controls are derived from the fourth and fifth rounds of NFHS. Data on *PMBJP* pharmacy locations comes from the Department of Pharmaceuticals, Ministry of Chemicals & Fertilizers, Government of India.

of the survey when their residence district experiences a *PMBJP* pharmacy entry. This effect is almost 17% of the sample mean for this age group during the pre-treatment period for treated sub-districts. Furthermore, I can reject the null hypothesis that the effect for older respondents is not statistically

different from children (p-value: 0.03) and middle-aged respondents (p-value: 0.00). The point estimates across the three age groups also are statistically different (p-value: 0.00).

After the entry of a *PMBJP* pharmacy in the residence sub-district, respondents of all ages report an increased likelihood of receiving treatment at a pharmacy. While the youngest respondents (age five or less) have the largest increase in the likelihood of receiving treatment at a pharmacy, I am unable to reject the null hypothesis that the effect on pharmacy treatment differs across any age category (p-value > 0.21). Only middle-aged respondents (aged between 15 and 30 years) are less likely to receive healthcare at a hospital or clinic when their residence sub-district experiences a *PMBJP* pharmacy opening. I can reject the null hypothesis that middle-aged respondents are affected similarly to young respondents (age five or less) (p-value: 0.05).

Taken together, estimates in column (3) and column (4) of Table 2 suggest that all age categories increase healthcare-seeking with a greater likelihood of the treatment received at a pharmacy. Only middle-aged respondents (aged between 15 and 30 years), however, substitute away from treatment at a hospital or clinic. I next examine if this substitution for middle-aged respondents away from treatment at a hospital or clinic can be explained by work arrangements or access to health insurance.

Can having access to health insurance moderate the effects of having a *PMBJP* pharmacy on healthcare-seeking behavior? I attempt to answer this question in column (1) and column (2) of Table 3. All estimates in Table 3 are from specification in Equation 1. While the point estimate for overall treatment is significant only for those respondents who do not have health insurance, I am unable to reject the null hypothesis that this point estimate is the same as that for the respondents who have health insurance (p-value: 0.12).

Point estimates in Panel B and Panel C of Table 3 suggest that it is only those respondents who do not have health insurance that substitute away from treatment at a hospital or clinic to treatment at a pharmacy.[9] Indeed, I am unable to reject the hypothesis that there is a one-to-one substitution between treatment at a hospital or clinic and treatment at a pharmacy for respondents without health insurance (p-value: 0.62). On the other hand, respondents who have health insurance do not undertake such substitution between alternate healthcare institutions. I also do not observe that there is a difference in how children respond to antibiotic consumption when their residence sub-district receives a *PMBJP* pharmacy depending on whether they have access to health insurance or not.

As reimbursement for healthcare expenses requires a prescription from a doctor and a bill from the pharmacy, the finding of substitution between hospital or clinic and pharmacy for treatment for respondents with no health insurance suggests that health insurance may have stemmed the flow away from healthcare-seeking at a hospital or clinic towards a pharmacy.

[9] I also note that the response of respondents with and without health insurance for receiving treatment at a hospital or clinic is statistically different (p-value: 0.04).

Table 3: Heterogeneity: Health Insurance, Education, and Employment

	Health Insurance		Education		Employment	
	No Health Insurance	Health Insurance	No Education	Some Education	Not Currently Working	Currently Working
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any Treatment						
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0340***	0.0044	0.0378*	0.0228**	0.0126	0.0224
	(0.0087)	(0.0203)	(0.0193)	(0.0105)	(0.0151)	(0.0162)
Adj. R2	0.072	0.116	0.085	0.073	0.086	0.079
Dep. Var. Mean	0.284	0.323	0.311	0.338	0.309	0.314
N	556,824	176,871	117,906	460,981	80,810	77,753
Panel B: Treatment at Pharmacy						
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0083***	0.0111***	0.0038	0.0123***	0.0060	0.0071
	(0.0030)	(0.0035)	(0.0053)	(0.0033)	(0.0074)	(0.0080)
Adj. R2	0.018	0.062	-0.004	0.023	0.044	0.080
Dep. Var. Mean	0.021	0.014	0.019	0.015	0.016	0.019
N	162,616	58,026	36,355	155,851	24,768	24,187
Panel C: Treatment at Hospital/Clinic						
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	-0.0150	0.0294	-0.0129	-0.0245*	-0.0723***	0.0296***
	(0.0141)	(0.0220)	(0.0204)	(0.0142)	(0.0188)	(0.0108)
Adj. R2	0.200	0.325	0.261	0.458	0.546	0.826
Dep. Var. Mean	0.769	0.766	0.798	0.773	0.746	0.249
N	162,616	58,026	36,355	155,851	24,768	24,187
Panel D: Antibiotic Taken						
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0291	0.0541				
	(0.0286)	(0.0467)				
Adj. R2	0.052	0.261				
Dep. Var. Mean	0.241	0.278				
N	22,345	4,893				

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each cell is a separate estimation of specification in Equation 1. Each specification also includes control variables for respondents' age, an indicator for the respondent to be male, and indicators for the respondent to be following Hinduism and Islam. The estimate in each cell is for the interaction of an indicator variable for whether the sub-district has any *PMBJP* pharmacy and an indicator variable for the respondent to have been surveyed in the fifth round of the National Family Health Survey (NFHS). All sub-districts that have at least one *PMBJP* pharmacy comprise the treatment group. The Independent variable in Panel A is an indicator variable for a sub-district having any *PMBJP* pharmacy. In Panel B, the independent variable is the count of *PMBJP* pharmacies. The dependent variable is in the column header. In Panel A, the dependent variable is an indicator variable for whether the respondent visits a health facility or camp for any reason for themselves or for any member of the household. In Panel B, the dependent variable is an indicator variable for whether the respondent reports visiting the pharmacy for treatment. In Panel C, the dependent variable is an indicator of whether the respondent reports visiting a hospital or clinic for treatment. The dependent variable in Panel B and Panel C is defined only if the respondent reports visiting a health facility or camp for any reason for themselves or for any member of the household. In Panel D, the dependent variable is an indicator variable for whether the respondent reports taking antibiotics for the ailment. The sample in Panel D is restricted to children under the age of five and if they seek treatment for diarrhea, fever, or cough. Column headers denote the subpopulation that comprises the analytical sample. All subpopulations are from the self-reported responses in the survey data. Data on outcome variables and controls are derived from the fourth and fifth rounds of NFHS. Data on *PMBJP* pharmacy locations comes from the Department of Pharmaceuticals, Ministry of Chemicals & Fertilizers, Government of India.

Do respondents who have some education change their healthcare-seeking behavior differentially than the respondents who have no education? I make progress towards answering this question in column (3)

and column (4) of Table 3. Both subgroups have a higher likelihood of receiving any treatment when their residence sub-district has a *PMBJP* pharmacy opening. At the same time, both subgroups are also more likely to report receiving treatment at a pharmacy but the estimate is statistically significant for subgroup with some education. The overall treatment and treatment at pharmacy effect does not differ across two subgroups (p-value > 0.15). The decline in treatment at a hospital or clinic is statistically significant for some education subgroup only. Moreover, there is no evidence that there is a substitution away from treatment at a hospital or clinic towards treatment at a pharmacy (p-value > 0.40). Weak statistical significance for overall healthcare-seeking behavior and non-significant effect for treatment at pharmacy and hospital or clinic for no education subgroup might be due to distrust or lack of information on the effectiveness of modern healthcare for this subgroup.

On examining whether the respondents who are currently working change their healthcare-seeking behavior overall or for receiving treatment at a pharmacy compared to respondents who are not currently working, I do not find any statistically significant change when the respondents' residence district has a *PMBJP* pharmacy entry. I am also unable to reject the null hypothesis that the effects for these two outcome variables differ in a statistically significant way across these subgroups (p-value> 0.53). Respondents who are not currently working, however, substitute away from treatment at a hospital or clinic. The effect of the decline in the likelihood of receiving healthcare at a hospital or clinic is multiple times higher than the increase in the likelihood of receiving healthcare at a pharmacy for this subgroup. As health insurance is often tied to employment, findings in column (7) of Table 3 echo findings in column (1).

Overall, results in Table 3 point to substitution between treatment at a pharmacy and treatment at a hospital or clinic for population subgroups that lack access to health insurance and have weak labor market attachment. Respondents who have some education do seek healthcare at a higher rate but are less likely to seek treatment at a hospital or clinic.

Next, I examine if the main effects vary across the wealth distribution of the respondents. To this end, I use DHS provided information on the wealth distribution of the households. I use wealth distribution in the survey round during which the households are interviewed to classify them in either the bottom three or top two wealth distribution quintiles. The estimates for all four outcome variables for the two subgroups are presented in Table 4. The point estimates show that relatively less affluent respondents have a higher likelihood of receiving treatment when their residence district experiences a *PMBJP* pharmacy entry. This increase is partially driven by the increase in treatment at pharmacies (Panel B) and these respondents do not substitute away from seeking treatment at a hospital or clinic for treatment at a pharmacy. The affluent subgroup, however, has no change in the likelihood of overall treatment (Panel A) but a higher likelihood of treatment at a pharmacy (Panel B) substituting away from treatment at a hospital or clinic (p-value: 0.83). Furthermore, the affluent subgroup also is more likely to have received antibiotics as part of their treatment regimen (Panel D, column (2)).

Table 4: Heterogeneity: Wealth

	Bottom Three Wealth Quintiles (1)	Top Two Wealth Quintiles (2)
Panel A: Any Treatment		
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0403***	0.0051
	(0.0095)	(0.0111)
Adj. R2	0.077	0.080
Dep. Var. Mean	0.278	0.309
N	374,385	359,340
Panel B: Treatment at Pharmacy		
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0077*	0.0138***
	(0.0042)	(0.0039)
Adj. R2	0.016	0.033
Dep. Var. Mean	0.021	0.018
N	107,879	112,772
Panel C: Treatment at Hospital/Clinic		
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0043	-0.0168
	(0.0154)	(0.0132)
Adj. R2	0.166	0.320
Dep. Var. Mean	0.742	0.794
N	107,879	112,772
Panel D: Antibiotic Taken		
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	-0.0161	0.0571*
	(0.0248)	(0.0336)
Controls	Yes	Yes
Sub-District FE	Yes	Yes
Survey Year $\times$ Month FE	Yes	Yes
Adj. R2	0.047	0.187
Dep. Var. Mean	0.228	0.275
N	15,780	11,524

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each cell is a separate estimation of specification in Equation 1. Each specification also includes control variables for respondents' age, an indicator for the respondent to be male, and indicators for the respondent to be following Hinduism and Islam. The estimate in each cell is for the interaction of an indicator variable for whether the sub-district has any *PMBJP* pharmacy and an indicator variable for the respondent to have been surveyed in the fifth round of the National Family Health Survey (NFHS). All sub-districts that have at least one *PMBJP* pharmacy comprise the treatment group. The Independent variable in Panel A is an indicator variable for a sub-district having any *PMBJP* pharmacy. In Panel B, the independent variable is the count of *PMBJP* pharmacies. The dependent variable is in the column header. In Panel A, the dependent variable is an indicator variable for whether the respondent visits a health facility or camp for any reason for themselves or for any member of the household. In Panel B, the dependent variable is an indicator variable for whether the respondent reports visiting the pharmacy for treatment. In Panel C, the dependent variable is an indicator of whether the respondent reports visiting a hospital or clinic for treatment. The dependent variable in Panel B and Panel C is defined only if the respondent reports visiting a health facility or camp for any reason for themselves or for any member of the household. In Panel D, the dependent variable is an indicator variable for whether the respondent reports taking antibiotics for the ailment. The sample in Panel D is restricted to children under the age of five and if they seek treatment for diarrhea, fever, or cough. Column headers denote the subpopulation that comprises the analytical sample. Households are classified in the wealth quintiles using the wealth distribution from the NFHS round they are interviewed. Data on outcome variables and controls are derived from the fourth and fifth rounds of NFHS. Data on *PMBJP* pharmacy locations comes from the Department of Pharmaceuticals, Ministry of Chemicals & Fertilizers, Government of India.

In Table A5, I find that the main effects are concentrated in the northern region of the country. Due to the small sample size, I am unable to precisely estimate effects for the other regions. On examining whether the main effects differ across religious subgroups, I find that respondents who report following

Hinduism are increasingly likely to seek healthcare when there is a *PMBJP* pharmacy entry in their residence district. This increase does not lead to a substitution away from treatment at a hospital or clinic to treatment at a pharmacy (p-value: 0.19). Hindu respondents are increasingly likely to report receiving treatment at a pharmacy and this estimate is highly statistically significant (Panel B, column (1)). Respondents following Christianity or other religions do not see an overall increase in treatment likelihood but substitute away from treatment at a hospital or clinic for treatment at a pharmacy (p-value > 0.84). Respondents following Christianity are also more likely to report receiving treatment at a pharmacy (Panel B, column (3)). Both Christian and other religion respondents are less likely to report receiving treatment at a hospital or clinic, post *PMBJP* pharmacy entry (Panel C, column (3) and column (4)).

Estimates in Table 5 also show that respondents who belong to Other Backward Classes (OBC) are more likely to report an increase in overall treatment along with an increase in the likelihood of receiving treatment at a pharmacy. These respondents do not substitute away from receiving treatment at a hospital or clinic for treatment at a pharmacy. I do not observe a statistically significant change for the other social groups for outcomes related to treatment.

To conclude, estimates in Table 5 show that amongst the broad social groups, only OBC respondents see an increase in the likelihood of overall treatment with an increase in the likelihood of the treatment to have been received at a pharmacy. There is no evidence that any social group substitutes treatment at a hospital or clinic for treatment at a pharmacy. Only respondents following Hinduism are more likely to seek treatment when their residence district has a *PMBJP* pharmacy entry along with an increase in the likelihood of receiving treatment at a pharmacy. While Christian and other religion respondents do not see a change in overall treatment likelihood, they do substitute treatment at a hospital or clinic for treatment at a pharmacy.

5.4 Mechanisms

While the absence of detailed data on reasons to seek healthcare is not available in the DHS, I am able to shed some light on the potential mechanisms that might be driving an increase in overall healthcare-seeking behavior with substitution away from treatment at a hospital or clinic to treatment at a pharmacy when the sub-district has a *PMBJP* pharmacy entry. As is highlighted in Section 5.3, economically and socially disadvantaged respondents (without health insurance access, not currently working, from minority religion or other backward classes) substitute away from treatment at a hospital or clinic for treatment at a pharmacy. Given the cost differences for treatment received at pharmacies and hospitals or clinics, it is likely that cost or transportation hurdles are a likely channel through which the main effects manifest. I aim to address if this is indeed the case in this section.

Table 5: Heterogeneity: Religion and Caste

	Religion				Caste			
	Hinduism	Islam	Christianity	Other Religion	Scheduled Caste	Scheduled Tribe	Other Backward Classes	General
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Any Treatment								
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0284**	0.0135	0.0263	-0.0260	0.0199	-0.0008	0.0619***	-0.0093
	(0.0114)	(0.0177)	(0.0245)	(0.0310)	(0.0158)	(0.0152)	(0.0195)	(0.0153)
Adj. R2	0.073	0.125	0.051	0.079	0.069	0.064	0.089	0.088
Dep. Var. Mean	0.289	0.330	0.249	0.309	0.301	0.260	0.301	0.302
N	535,826	109,816	52,114	35,523	131,352	130,634	289,738	150,702
Panel B: Treatment at Pharmacy								
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0114***	-0.0039	0.0245**	0.0009	-0.0024	0.0050	0.0180***	-0.0015
	(0.0028)	(0.0058)	(0.0099)	(0.0140)	(0.0045)	(0.0044)	(0.0037)	(0.0050)
Adj. R2	0.020	0.032	0.003	0.016	0.030	0.030	0.014	0.034
Dep. Var. Mean	0.018	0.024	0.019	0.028	0.022	0.013	0.019	0.022
N	158,669	36,904	13,592	11,076	40,244	35,207	88,949	46,263
Panel C: Treatment at Hospital/Clinic								
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0057	0.0105	-0.0421*	-0.0602***	-0.0230	0.0030	-0.0035	-0.0178
	(0.0137)	(0.0282)	(0.0216)	(0.0206)	(0.0210)	(0.0160)	(0.0172)	(0.0216)
Adj. R2	0.224	0.171	0.252	0.350	0.209	0.295	0.167	0.388
Dep. Var. Mean	0.760	0.781	0.804	0.808	0.761	0.757	0.764	0.790
N	158,669	36,904	13,592	11,076	40,244	35,207	88,949	46,263
Panel D: Antibiotic Taken								
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0387	-0.0122	0.0049	-0.1880	0.1761***	-0.0400	0.0030	-0.0964**
	(0.0351)	(0.0507)	(0.1039)	(0.1355)	(0.0476)	(0.0566)	(0.0478)	(0.0419)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.038	0.136	0.128	0.325	0.250	0.105	0.025	0.218
Dep. Var. Mean	0.226	0.258	0.382	0.309	0.224	0.292	0.237	0.252
N	19,096	4,965	2,159	1,019	4,907	4,692	10,746	4,718

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each cell is a separate estimation of specification in Equation 1. Each specification also includes control variables for respondents' age, an indicator for the respondent to be male, and indicators for the respondent to be following Hinduism and Islam. The estimate in each cell is for the interaction of an indicator variable for whether the sub-district has any *PMBJP* pharmacy and an indicator variable for the respondent to have been surveyed in the fifth round of the National Family Health Survey (NFHS). All sub-districts that have at least one *PMBJP* pharmacy comprise the treatment group. The Independent variable in Panel A is an indicator variable for a sub-district having any *PMBJP* pharmacy. In Panel B, the independent variable is the count of *PMBJP* pharmacies. The dependent variable is in the column header. In Panel A, the dependent variable is an indicator variable for whether the respondent visits a health facility or camp for any reason for themselves or for any member of the household. In Panel B, the dependent variable is an indicator variable for whether the respondent reports visiting the pharmacy for treatment. In Panel C, the dependent variable is an indicator of whether the respondent reports visiting a hospital or clinic for treatment. The dependent variable in Panel B and Panel C is defined only if the respondent reports visiting a health facility or camp for any reason for themselves or for any member of the household. In Panel D, the dependent variable is an indicator variable for whether the respondent reports taking antibiotics for the ailment. The sample in Panel D is restricted to children under the age of five and if they seek treatment for diarrhea, fever, or cough. Column headers denote the subpopulation that comprises the analytical sample. All subpopulations are from the self-reported responses in the survey data. Data on outcome variables and controls are derived from the fourth and fifth rounds of NFHS. Data on *PMBJP* pharmacy locations comes from the Department of Pharmaceuticals, Ministry of Chemicals & Fertilizers, Government of India.

I make use of detailed questions in the DHS regarding the reasons for which the women respondents report not using contraceptives, family planning methods, and seeking treatment for pregnancy complications. I estimate specification in Equation 1 for three outcome variables. The first outcome variable is

an indicator variable for whether the respondent reports discontinuing any contraceptive in the last five years either due to cost or transport reasons. This variable is defined only for those respondents who report discontinuing any contraceptive in the last five years. The second dependent variable is an indicator variable for whether the respondent reports not using any family planning method despite not wanting to have any more children either due to cost or transport reasons. This variable is defined only for those respondents who either do not want to have another child soon or those who do not want to have another child along with reporting non-use of any family planning method. The final dependent variable is the sum of the previous two variables along with an indicator variable for whether the respondent reports not seeking treatment for pregnancy complications either due to cost or transport reasons. The indicator variable for not seeking treatment due to pregnancy complications is defined only for those respondents who have complications due to abortion for any birth in the last five years from the date of the survey. I present results from estimating this specification in Table 6.

Table 6: Mechanisms: Finance

	Contraceptive Use (1)	Family Planning (2)	Finance Index (3)
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	-0.0062	-0.0242***	-0.0158***
	(0.0081)	(0.0062)	(0.0050)
Adj. R2	0.054	0.080	0.047
Dep. Var. Mean	0.036	0.029	0.035
N	55,418	76,510	121,790

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each cell is a separate estimation of specification in Equation 1. Each specification also includes control variables for respondents' age, an indicator for the respondent to be male, and indicators for the respondent to be following Hinduism and Islam. The estimate in each cell is for the interaction of an indicator variable for whether the sub-district has any *PMBJP* pharmacy and an indicator variable for the respondent to have been surveyed in the fifth round of the National Family Health Survey (NFHS). All sub-districts that have at least one *PMBJP* pharmacy comprise the treatment group. The dependent variable is displayed in the column header. The dependent variable in column (1) is an indicator variable for whether the respondent reports discontinuing any contraceptive in the last five years either due to cost or transport reasons. This variable is defined only for those respondents who report discontinuing any contraceptive in the last five years. The dependent variable in column (2) is an indicator variable for whether the respondent reports not using any family planning method despite not wanting to have any more children either due to cost or transport reasons. This variable is defined only for those respondents who either do not want to have another child soon or those who do not want to have another child along with reporting non-use of any family planning method. The dependent variable in column (3) is the sum of variables in column (1) and column (2) along with an indicator variable for whether the respondent reports not seeking treatment for pregnancy complication either due to cost or transport reasons. The indicator variable for not seeking treatment due to pregnancy complication is defined only for those respondents who have complication due to abortion for any birth in the last five years from the date of survey. Data on outcome variables and controls are derived from the fourth and fifth rounds of NFHS. Data on *PMBJP* pharmacy locations comes from the Department of Pharmaceuticals, Ministry of Chemicals & Fertilizers, Government of India.

Estimates in Table 6 indicate that when respondents' residence district experiences an entry of a *PMBJP* pharmacy, the likelihood of reporting non-use of reproductive care due to cost or transport reasons

declines. The point estimates in column (2) and column (3) are highly statistically significant and suggest that an increase in healthcare-seeking behavior after the pharmacy entry could be driven by reduced transport costs and better access to one institution providing healthcare services. Quantitatively, the point estimate in column (2) is almost a 79% decline over the pre-treatment period mean for the sub-districts that eventually get a *PMBJP* pharmacy. The decline in the finance index in the last column is almost 50% over the pre-treatment period mean for the treated sub-districts.

6 Discussion and Conclusion

I examine if improving access to pharmacies influences the overall healthcare-seeking behavior of the affected respondents and if this change is driven by substitution patterns across various healthcare institutions. Leveraging spatial and temporal variation emanating from a nationwide policy in India, I show that better access to pharmacies leads to an increase in some treatment at a healthcare institution. This change, however, masks a substitution between treatment at a hospital or clinic and pharmacy. I establish the robustness of this conclusion to a host of empirical checks. I uncover significant heterogeneities in the healthcare-seeking behavior across subpopulations and find that existing disparities in healthcare might get accentuated due to improved access to pharmacies. I shed light on finance and transport related barriers as a likely mechanism leading to the observed changes in healthcare-seeking behavior.

This work provides crucial evidence on the unintended consequences of policies that seek to improve access to healthcare institutions. In a setting where there are supply and demand frictions for healthcare provision and access, some well-intentioned policies may worsen the existing disparities in healthcare use. Perhaps a greater emphasis on enforcing the rules and regulations regarding the dispensation of drugs can dampen these perverse effects. As organizations around the world address increasing antimicrobial resistance in their populations, this paper points to the role of improved access to underregulated pharmacies in driving the resistance to existing drugs treating bacterial infections.

My work has several limitations. Lacking precise information on the start date of pharmacies, I rely on rather strong assumptions to determine the timing of exposure. The lack of detailed information on healthcare utilization prevents me from uncovering other potential mechanisms leading to the observed changes. As information on antibiotic consumption is available for children who are under the age of five, my estimates on outcomes related to antibiotic consumption are imprecisely measured. I hope future work can address some of these shortcomings.

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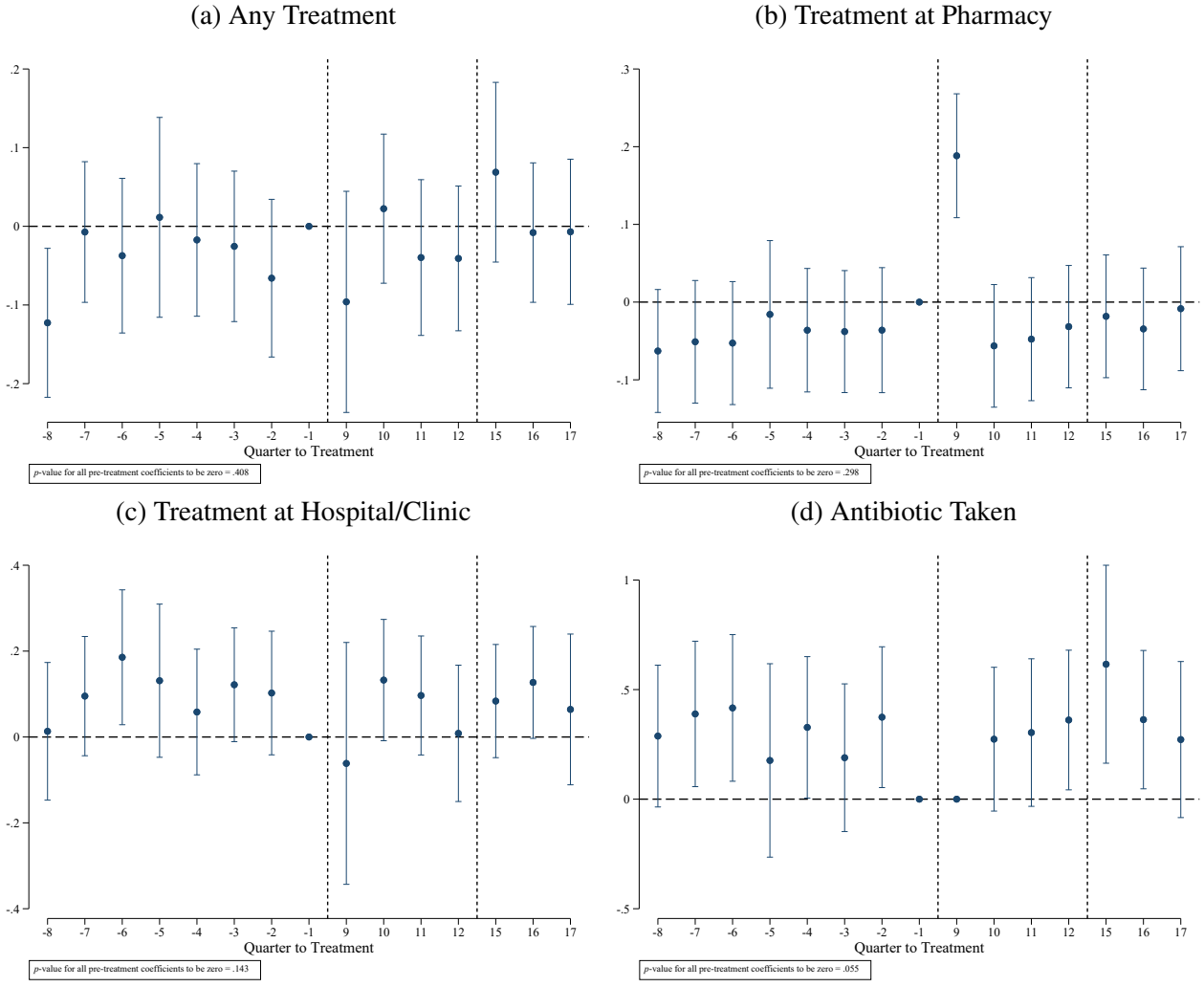
Appendices

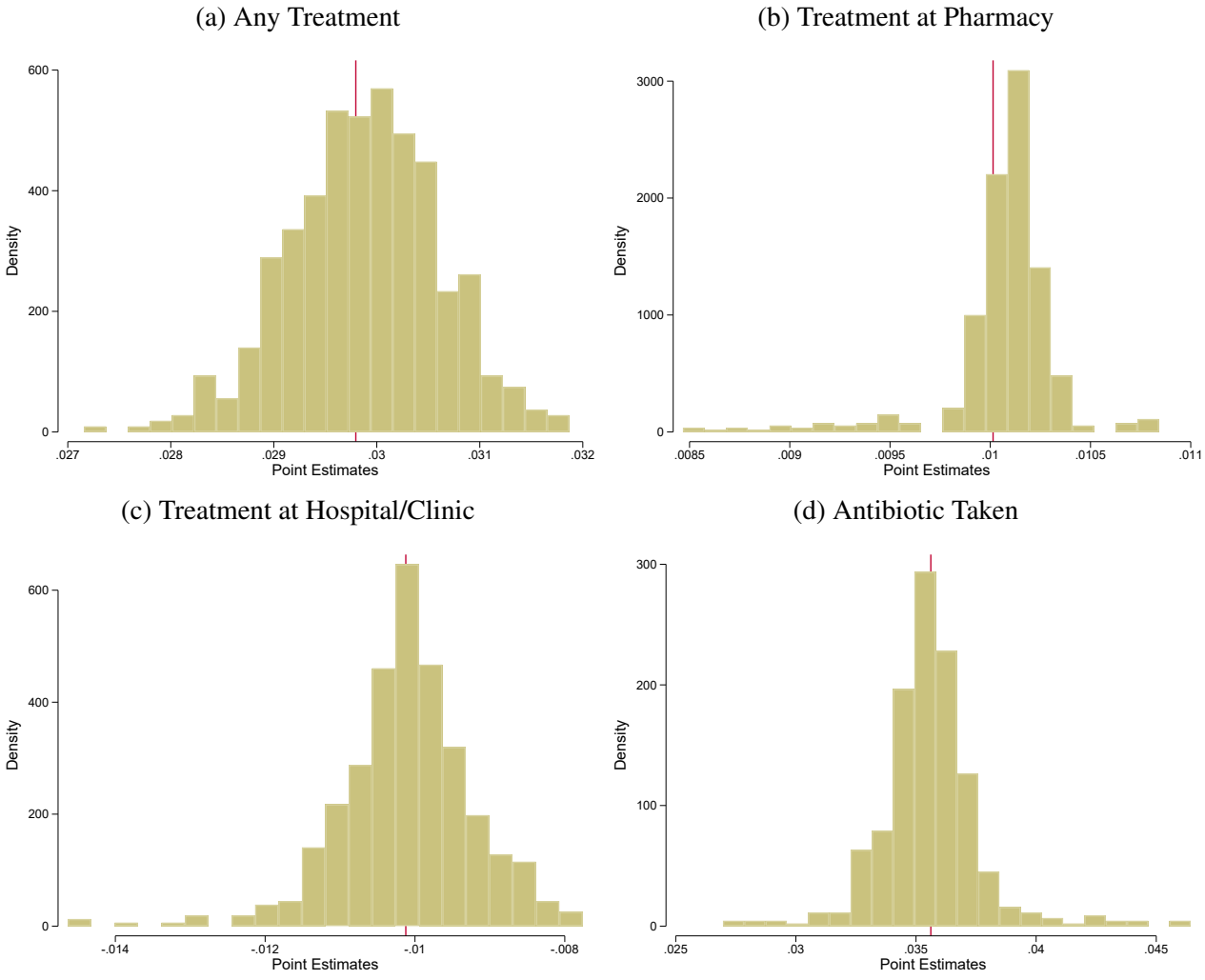
Appendix A Figures and Tables

Figure A1: Event-study Estimates



Note: This figure presents event-study estimates and 95% confidence intervals from the estimation of specification in Equation 2. Estimates for all four main outcome variables are presented. The first vertical dashed line on the horizontal axis corresponds to the first quarter after the latest quarter in which any interview is conducted in the fourth round of the National Family Health Survey (NFHS). The second vertical dashed line on the horizontal axis corresponds to the two quarters during which no survey was fielded due to COVID-19. The outcome variable is in the panel caption. Refer to Table 1 for information on the dependent variables. p-value in the panel notes is from a joint hypothesis test of all pre-treatment coefficients being zero. Data comes from the fourth and fifth rounds of NFHS.

Figure A2: Randomization Inference



Note: This figure presents the distribution of point estimates from estimating specification in Equation 1. The main point estimate is depicted as the red vertical line. One percent of the rural clusters with a five-kilometer buffer are randomly dropped on each iteration. This process is repeated 500 times. The main point estimate for each outcome variable is centered approximately around the median of the distribution of point estimates. This suggests that misclassification of rural clusters that are displaced up to 10 kilometers does not drive the main effect.

Table A1: Having any *Pradhan Mantri Bhartiya Janaushadhi Pariyojana (PMBJP)* Pharmacy Probit Regression Estimates

	Estimate (SE)
Total Population	0.467
	(0.438)
Male Population	-0.906
	(0.781)
Population (0-6 Years)	-0.856
	(0.621)
Scheduled Castes Population	-0.283***
	(0.103)
Scheduled Tribes Population	0.025
	(0.066)
Literate Population	1.290***
	(0.163)
Total Workers	-0.408***
	(0.157)
Pseudo R2	0.232
N	5,939

Notes: * p<.10 ** p<.05 *** p<.01. Estimates are from a cross-sectional Probit regression where the outcome is an indicator for whether the sub-district has any *Pradhan Mantri Bhartiya Janaushadhi Pariyojana (PMBJP)* Pharmacy. Regressors are from 2011 Population Census. All regressors are in 100000 persons.

Table A2: Sub-District Characteristics, Outcomes, and Individual Characteristics Mean

	All Sub-Districts	Pharmacy Sub-Districts	Non-Pharmacy Sub-Districts Unweighted	Non-Pharmacy Sub-Districts P-Weighted
Panel A: Sub-District Characteristics				
Total Population	2.0054	3.4388	1.2108	3.2264
Male Population	1.0324	1.7749	0.6208	1.6586
Population (0-6 Years)	0.2737	0.4499	0.1761	0.4855
Scheduled Castes Population	0.3343	0.5649	0.2065	0.5849
Scheduled Tribes Population	0.1735	0.1857	0.1667	0.1937
Literate Population	1.2601	2.2801	0.6947	1.8674
Total Workers	0.7990	1.3115	0.5149	1.1647
Number of Sub-Districts	5,969	2,127	3,842	3,842
Panel B: Outcomes				
Any Treatment	0.3281	0.3460	0.3241	0.4048
Treatment at Pharmacy	0.0277	0.0216	0.0190	0.0312
Treatment at Hospital/Clinic	0.7352	0.7622	0.7531	0.8022
Antibiotic Taken	0.2364	0.2425	0.2346	0.2997
Panel C: Individual Characteristics				
Age (in months)	23.2703	24.1125	23.2380	22.2616
Sex				
Female	0.7693	0.7720	0.7698	0.7999
Male	0.2307	0.2280	0.2302	0.2001
Religion				
Hinduism	0.7377	0.7284	0.7066	0.6966
Islam	0.1409	0.1728	0.1344	0.1252
Other Religions	0.1214	0.0988	0.1589	0.1781
Caste Category				
Scheduled Caste	0.1888	0.1856	0.1604	0.1756
Scheduled Tribe	0.1942	0.1226	0.3039	0.1776
Other Backward Classes	0.4082	0.4367	0.3642	0.5108
Wealth Quintiles				
Poorest	0.2057	0.0993	0.2097	0.2574
Poorer	0.2185	0.1342	0.2198	0.2079
Middle	0.2084	0.1846	0.2120	0.1937
Richer	0.1912	0.2529	0.1972	0.1935
Richest	0.1763	0.3291	0.1613	0.1476
Education Level				
No Education	0.2606	0.2001	0.2664	0.3036
Primary	0.1264	0.1123	0.1351	0.1081
Secondary	0.4930	0.5062	0.4886	0.4476
Higher	0.1200	0.1814	0.1099	0.1407

Notes: Data for sub-district characteristics are derived from 2011 Population Census. All sub-district characteristics are in 100000 persons. Outcomes and individual characteristics data comes from National Family Health Survey (NFHS) round four. In the last column weighting is done to ensure comparability between sub-districts that have any *Pradhan Mantri Bhartiya Janaushadhi Pariyojana (PMBJP)* Pharmacy and those that do not.

Table A3: Robustness Checks: Extensive Margin

	Any Treatment (1)	Treatment at Pharmacy (2)	Treatment at Hospital/Clinic (3)	Antibiotic Taken (4)
Panel A: Baseline Estimates				
$\mathbb{1}$(Any *PMBJP* Pharmacy)	0.0296***	0.0099***	-0.0105	0.0336
	(0.0090)	(0.0026)	(0.0126)	(0.0269)
Adj. R2	0.075	0.021	0.213	0.060
Dep. Var. Mean	0.293	0.020	0.768	0.247
N	733,782	220,941	220,941	27,922
Panel B: Drop Children Under Five				
$\mathbb{1}$(Any *PMBJP* Pharmacy)	0.0265**	0.0098***	-0.0218*	
	(0.0110)	(0.0028)	(0.0132)	
Adj. R2	0.076	0.017	0.417	
Dep. Var. Mean	0.333	0.016	0.777	
N	578,994	192,590	192,590	
Panel C: Control for Number of Pharmacies in the Sub-district				
$\mathbb{1}$(Any *PMBJP* Pharmacy)	0.0340***	0.0109***	-0.0129	0.0437
	(0.0094)	(0.0028)	(0.0134)	(0.0283)
Adj. R2	0.074	0.020	0.205	0.060
Dep. Var. Mean	0.296	0.020	0.770	0.241
N	640,292	194,046	194,046	24,243
Panel D: Cluster SEs at District-level				
$\mathbb{1}$(Any *PMBJP* Pharmacy)	0.0296***	0.0099***	-0.0105	0.0336
	(0.0090)	(0.0026)	(0.0127)	(0.0279)
Adj. R2	0.075	0.021	0.213	0.060
Dep. Var. Mean	0.293	0.020	0.768	0.247
N	733,782	220,941	220,941	27,922
Panel E: Add State Time Trends				
$\mathbb{1}$(Any *PMBJP* Pharmacy)	0.0078	0.0030	-0.0123	0.0343*
	(0.0081)	(0.0024)	(0.0094)	(0.0196)
Adj. R2	0.078	0.023	0.214	0.065
Dep. Var. Mean	0.293	0.020	0.768	0.247
N	733,782	220,941	220,941	27,922

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses.

Table A4: Robustness Checks: Intensive Margin

	Any Treatment (1)	Treatment at Pharmacy (2)	Treatment at Hospital/Clinic (3)	Antibiotic Taken (4)
Panel A: Baseline Estimates				
# *PMBJP* Pharmacies	0.0004	0.0002***	-0.0001	0.0009
	(0.0003)	(0.0001)	(0.0002)	(0.0008)
Adj. R2	0.075	0.021	0.213	0.060
Dep. Var. Mean	0.293	0.020	0.768	0.247
N	733,782	220,941	220,941	27,922
Panel B: Drop Children Under Five				
# *PMBJP* Pharmacies	0.0004	0.0002***	-0.0001	
	(0.0003)	(0.0001)	(0.0002)	
Adj. R2	0.076	0.017	0.417	
Dep. Var. Mean	0.333	0.016	0.777	
N	578,994	192,590	192,590	
Panel C: Control for Number of Pharmacies in the Sub-district				
# *PMBJP* Pharmacies	0.0004	0.0002***	0.0000	0.0010
	(0.0003)	(0.0001)	(0.0003)	(0.0008)
Adj. R2	0.074	0.020	0.205	0.059
Dep. Var. Mean	0.296	0.020	0.770	0.241
N	640,292	194,046	194,046	24,243
Panel D: Cluster SEs at District-level				
# *PMBJP* Pharmacies	0.0004	0.0002***	-0.0001	0.0009
	(0.0003)	(0.0001)	(0.0002)	(0.0008)
Adj. R2	0.075	0.021	0.213	0.060
Dep. Var. Mean	0.293	0.020	0.768	0.247
N	733,782	220,941	220,941	27,922
Panel E: Add State Time Trends				
# *PMBJP* Pharmacies	-0.0000	0.0001***	-0.0000	0.0008
	(0.0002)	(0.0000)	(0.0002)	(0.0007)
Adj. R2	0.078	0.023	0.214	0.065
Dep. Var. Mean	0.293	0.020	0.768	0.247
N	733,782	220,941	220,941	27,922

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses.

Table A5: Heterogeneity: Region

	North	North-East	East	West	South
	(1)	(2)	(3)	(4)	(5)
Panel A: Any Treatment					
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0181*	-0.0188	0.0080	-0.0308	-0.0032
	(0.0108)	(0.0167)	(0.0206)	(0.0230)	(0.0251)
Adj. R2	0.076	0.031	0.060	0.060	0.113
Dep. Var. Mean	0.306	0.242	0.265	0.247	0.335
N	393,322	82,566	52,974	88,900	116,019
Panel B: Treatment at Pharmacy					
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0128***	-0.0004	-0.0085	-0.0033	0.0042*
	(0.0034)	(0.0084)	(0.0127)	(0.0035)	(0.0025)
Adj. R2	0.019	0.011	0.076	0.015	0.017
Dep. Var. Mean	0.023	0.029	0.042	0.006	0.003
N	123,178	21,068	14,440	22,625	39,628
Panel C: Treatment at Hospital/Clinic					
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	-0.0265*	-0.0209	0.0285	0.0058	-0.0196
	(0.0152)	(0.0182)	(0.0276)	(0.0227)	(0.0187)
Adj. R2	0.184	0.237	0.264	0.339	0.398
Dep. Var. Mean	0.753	0.794	0.728	0.768	0.819
N	123,178	21,068	14,440	22,625	39,628
Panel D: Antibiotic Taken					
$\mathbb{1}$ (Any *PMBJP* Pharmacy)	0.0859***	-0.0018	-0.0628	-0.0494	-0.0698
	(0.0325)	(0.0667)	(0.0699)	(0.0554)	(0.0561)
Controls	Yes	Yes	Yes	Yes	Yes
Sub-District FE	Yes	Yes	Yes	Yes	Yes
Survey Year × Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.068	0.084	0.189	0.161	0.184
Dep. Var. Mean	0.229	0.342	0.268	0.207	0.268
N	15,798	3,237	2,069	3,287	3,529

Notes: Heteroskedasticity robust standard errors clustered by the sub-district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each cell is a separate estimation of specification in Equation 1. Each specification also includes control variables for respondents' age, an indicator for the respondent to be male, and indicators for the respondent to be following Hinduism and Islam. The estimate in each cell is for the interaction of an indicator variable for whether the sub-district has any *PMBJP* pharmacy and an indicator variable for the respondent to have been surveyed in the fifth round of the National Family Health Survey (NFHS). All sub-districts that have at least one *PMBJP* pharmacy comprise the treatment group. The Independent variable in Panel A is an indicator variable for a sub-district having any *PMBJP* pharmacy. In Panel B, the independent variable is the count of *PMBJP* pharmacies. The dependent variable is in the column header. In Panel A, the dependent variable is an indicator variable for whether the respondent visits a health facility or camp for any reason for themselves or for any member of the household. In Panel B, the dependent variable is an indicator variable for whether the respondent reports visiting the pharmacy for treatment. In Panel C, the dependent variable is an indicator of whether the respondent reports visiting a hospital or clinic for treatment. The dependent variable in Panel B and Panel C is defined only if the respondent reports visiting a health facility or camp for any reason for themselves or for any member of the household. In Panel D, the dependent variable is an indicator variable for whether the respondent reports taking antibiotics for the ailment. The sample in Panel D is restricted to children under the age of five and if they seek treatment for diarrhea, fever, or cough. Column headers denote the subpopulation that comprises the analytical sample. States and union territories classified in the north region are Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu and Kashmir, Ladakh, Punjab, Rajasthan, Chhattisgarh, Madhya Pradesh, Uttarakhand, and Uttar Pradesh. States and union territories classified in the north-east region are Assam, Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura. States and union territories classified in the east region are Bihar, Jharkhand, Odisha, and West Bengal. States and union territories classified in the western region are Dadra and Nagar Haveli, Daman and Diu, Goa, Gujarat, and Maharashtra. States and union territories classified in the south region are Andhra Pradesh, Karnataka, Kerala, Puducherry, Tamil Nadu, Telangana, Andaman and Nicobar Islands, and Lakshadweep. Data on outcome variables and controls are derived from the fourth and fifth rounds of NFHS. Data on *PMBJP* pharmacy locations comes from the Department of Pharmaceuticals, Ministry of Chemicals & Fertilizers, Government of India.