Improving Health Outcomes Through Mid-level Providers: Evidence from India's Large-Scale Primary Healthcare Expansion

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Abstract

This paper examines the stepwise rollout of one of the world's largest healthcare reforms: the assignment of a new mid-level provider (non-physician practitioner) to each public primary healthcare facility across rural India, impacting healthcare provision for more than 450 million people. We use a matched difference-in-differences strategy based on provider assignment rules to study how expansion of basic outpatient care and increased screening for chronic diseases affects health outcomes. Using large-scale administrative data covering all villages in the state of Rajasthan, we document that elderly deaths are 12% lower in treated areas one year post-reform. Monthly patient loads at public primary healthcare facilities increase by 68% and diagnoses of hypertension and diabetes at these facilities increase by 67% and 62%, respectively. We observe no effects on maternal and child outcomes, suggesting that the new focus on chronic diseases did not divert resources from existing maternal and child health services. Results from audits and patient exit surveys document improvements to public healthcare quality and availability of services. We also survey private providers and find that the increased competition from the public sector incentivized private providers to invest in quality upgrades. Strengthening the provision of public primary healthcare through the assignment of new mid-level providers can be highly cost-effective, generating 51 dollars in private benefits for every government dollar spent.

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1 Introduction

Across the globe, mortality profiles are rapidly changing with economic development and an aging population. In India, where this study takes place, the share of total deaths due to child mortality has declined by almost three-quarters over the past two decades, while the share of deaths due to elderly mortality has steadily increased (Global Burden of Disease Study, 2019). Chronic diseases are now the leading cause of death in most low- and middle-income countries, with hypertension contributing to 1.6 million deaths every year in India alone (WHO, 2023).[1] Yet healthcare systems, which have typically focused on maternal and child health, are often ill-equipped to meet this new reality (Islam et al., 2014). Restructuring public health services to meet the needs of an aging population is therefore an urgent research and policy problem, but there is limited evidence on how to do so cost-effectively and at scale.

This paper helps to fill this knowledge gap by studying a large-scale reform to India's public healthcare system. The reform, which impacted healthcare provision for over 450 million people, involved posting a mid-level provider (non-physician practitioner) to every subcenter (rural health outpost) across the country. These mid-level providers, also known as *community heath officers* (CHOs), are mandated with providing basic adult outpatient care and screening for chronic diseases.[2] By strengthening primary care at the local level, the reform has the potential to prevent premature adult mortality through early diagnosis and by reducing delays in access to treatments and referrals. However, the magnitude and even existence of impacts on adult health outcomes from such a reform are unclear since labor inputs may not be sufficient to overcome demand-side constraints (Dupas, 2011) or limited state capacity (Chaudhury et al., 2006; Banerjee et al., 2008). In addition, the expanded focus on adult health carries important risks, since it may divert attention from still pressing

[1]The economic costs of chronic diseases are especially high in low- and middle-income countries, where chronic diseases occur at earlier ages (Rashmi and Mohanty, 2023) and patients die younger than their counterparts in high-income countries (Stuckler, 2008). Estimates suggest that the economic impact of the five main chronic diseases in India between 2012 and 2030 will be USD 12.7 trillion (Bloom et al., 2014), adjusted to 2022 dollars.

[2]Subcenters, the lowest level of primary care facilities, were previously staffed only by a low-level *auxiliary nurse midwife* (ANM), whose primary focus is maternal and newborn health.

maternal and newborn health needs.[3]

In order to study how the posting of mid-level providers affects the provision of health services and outcomes, we focus on the rollout of the reform within Rajasthan, one of India's largest and poorest states. Our identification strategy exploits the stepwise rollout of the new mid-level providers across the state, using a matched difference-in-differences design that is informed by the rules of the provider assignment process. Due to budget constraints, the government of Rajasthan could fill only two-thirds of eligible provider vacancies in the first wave of program implementation (March 2022). The selection of subcenters to the first wave was ad hoc: local government officials were told to decide on assignments within their district by taking into account providers' previous place of residence and subcenter locations, but without any further information to guide their decisions. This resulted in quasi-random variation in assignments to subcenters conditional on a subcenter's location. In our preferred specification, we use inverse probability weighting based on district fixed effects and geographical information to create matched treatment and control samples. Consistent with our knowledge of the assignment rule, we find that a propensity score function that uses only this information is sufficient to create balance along other observable subcenter characteristics.

Our analysis relies on large-scale administrative health data for all 46,560 villages in Rajasthan, which we supplement with two rounds of original survey data on public providers, private providers, and households across 193 villages in the state. Our novel administrative data covers monthly patient loads and service utilization for the universe of public primary healthcare facilities as well as mortality outcomes for all villages in a subcenter's catchment area. The primary survey data we collect further allows us to measure how the reform affected hospitalization rates, availability of services, and healthcare quality in the public and private sectors. Additionally, in collaboration with a local NGO, we collect data on households' provider choices as part of an ongoing healthcare household census that is currently being administered in all villages within the state.

[3]Previous research in this area often focuses on task shifting, i.e., the reallocation of tasks from physicians to lower-level healthcare providers. Past studies have shown that task shifting can lead to the overloading of healthcare workers, making them neglect traditional services such as postnatal home visits (Smith et al., 2014; Olaniran et al., 2019). Other work also documents how HIV donor funding crowded out maternal and child health services in some settings (Grépin, 2012).

We find that the introduction of mid-level providers to local health outposts has a dramatic impact on the health of elderly individuals. Using our statewide data on mortality outcomes, we find that the posting of a CHO reduced the number of elderly (age 56+) deaths in treated areas by 12% within the first twelve months. Mortality outcomes for other age groups are not impacted. Results from our household survey further show a decline in hospitalizations, also driven by a decrease in hospitalizations among the elderly. This focused impact on the health of older adults is consistent with the fact that elderly health outcomes are in general most sensitive to improved outpatient care and screening for chronic diseases (Bailey and Goodman-Bacon, 2015), a primary focus of the new CHOs.

Improvements in health outcomes are driven by a large increase in the utilization of healthcare services: administrative data shows that the average number of patient visits rose by 68% per quarter at subcenters where a CHO was posted. Consistent with higher screening rates, the number of visits to subcenters by patients diagnosed with hypertension and diabetes also increased by 67% and 62%, respectively. Survey data suggests that the increase in patient visits is driven by individuals who would not have otherwise seen a healthcare provider and who are more likely to be from a disadvantaged minority.

Policymakers and researchers have emphasized the risk that reorienting healthcare systems to provide adequate services for an aging population could undermine recent gains in maternal and child health outcomes (Olaniran et al., 2019). Prior to the posting of the new mid-level providers, India's subcenters were staffed only by low-level auxiliary nurse midwives, whose focus was maternal and child health. Reassuringly, we find that the posting of CHOs did not divert attention from these existing services. Our results indicate that the reform had no impact on infant mortality or the number of low-birthweight children and we find no treatment effects on an index of seven maternal and child health services, including pre- and postnatal care visits and the number of fully immunized children.

We show that our results are robust to various sensitivity tests, including alternative matching strategies, sample restrictions, and difference-in-differences estimators. We also continue to find effects when we instead use a difference-in-differences design that compares treatment subcenters with the closest control subcenter in the area. Similar pre-trends provide further evidence against concerns that differential trends between treatment and control units could be driving our results.

Since the new CHOs have higher medical degrees than the existing ANMs, the reform might not only reduce capacity constraints but also improve the quality of healthcare services at subcenters.[4] Using our public provider surveys, we first show that the increase in capacity translated into a higher availability of healthcare services: treatment subcenters are 64% more likely to be open during unannounced audit visits. Suggestive evidence from patient exit surveys further shows that the new CHOs increase patient satisfaction, the number of examination questions asked, and referral rates. A rising share of outpatient care patients whose blood pressure was measured also indicates the importance of "opportunistic screening", where at-risk patients are automatically screened whenever they visit the healthcare facility. Limited variation in treatment effects based on two proxies for provider quality (vignette performance and entry-exam ranking) points to increased availability of services as the main driver of our results. This is consistent with the idea that screening for chronic diseases and the treatment of basic symptoms does not require high-level medical knowledge, making access to services and not quality of care the binding constraint for elderly patients.

Survey data further shows that private (mostly informal) providers in treatment areas respond to the increased competition from the public sector by investing in quality upgrades. This effect is especially pronounced among providers that are located closer to treatment subcenters, consistent with a decrease in market power driving the effects. Private providers near treatment subcenters increase the number of training workshops they attend, are more likely to be currently enrolled in a degree program, and have more coworkers. We observe no changes in the total number of operational private providers, prices, and the number of patients. We also find no evidence for concerns that increased competition could encourage the use of potentially harmful practices, including the overuse of injections and antibiotics at private providers.

We use the Marginal Value of Public Funds (MVPF) framework to calculate the cost-effectiveness analysis of the healthcare reform (Hendren and Sprung-Keyser, 2020). On the government costs side, we account for the salaries of the new CHOs and increased spending

[4]We confirm that the posting of the new providers does not affect other margins at treatment subcenters, like the availability of equipment or medicine.

on medicines as they are provided for free at public primary healthcare facilities. On the government benefits side, we account for decreased public spending on hospitalizations. For private benefits, we consider the decrease in elderly deaths and reduced out-of-pocket spending on hospitalizations. We estimate that the reform generates 51 dollars in private benefits for every government dollar spent. The costs per life-year saved are equal to 1.3 times the GDP per capita in India. As a benchmark, the World Health Organization considers interventions cost-effective if the costs are up to three times GDP per life-year saved (Patenaude et al., 2019).

We further find that the treatment effects are concentrated in subcenters located farthest from the nearest physician-staffed public primary healthcare clinic, as patients have access to fewer alternative healthcare providers. A back-of-the-envelope calculation suggests that elderly deaths could have declined by 16% instead of 12% if the government had prioritized the most remote subcenters when deciding where to assign the first cohort of mid-level providers. Larger improvements in health outcomes in subcenters with electricity further indicate potential complementarities between labor inputs and physical infrastructure.

This paper contributes to three bodies of work. To the best of our knowledge, we are the first to show how a large-scale expansion of adult public primary healthcare through mid-level providers can decrease elderly mortality in a low- or middle-income setting. Previous research has focused on constraints to preventive care from a demand-side perspective.[5] Our results supplement existing findings that document how researcher-led screening initiatives for specific chronic diseases like hypertension and cancer (Sankaranarayanan et al., 2005; Shastri et al., 2014) as well as improved access to health insurance (Sood et al., 2014; Gruber et al., 2023) can lead to a decrease in mortality. We document that large-scale government programs can also achieve substantial improvements in health outcomes. Our study is closely related to Bailey and Goodman-Bacon (2015) and Mora-Garcia et al. (2022), who find that the construction of new public primary healthcare facilities decreased elderly mortality in the US and in Costa Rica. We show that strengthening existing facilities through the posting of

[5]Studies have shown that patients underinvest in preventive health because they are optimistic about their own health (Kim and Niederdeppe, 2013), want to avoid stigma (Birje et al., 2022), lack information (Carrieri and Wuebker, 2016), are present-biased (Bai et al., 2021), want to avoid information (Oster et al., 2013; Li et al., 2021), and have limited access to treatment options if diagnosed with a health condition (Okeke et al., 2013).

an additional mid-level provider can achieve similar improvements in health outcomes within a short time frame, even in a setting where state capacity is low.[6]

Second, we contribute to the literature on how to improve the provision of public healthcare. Most of the existing work in developing countries focuses on improving the performance of existing healthcare workers through monitoring and financial incentives (Gertler and Vermeersch, 2013; Björkman and Svensson, 2009; Christensen et al., 2020). Only a limited number of studies assess how adding physicians or mid-level providers to public facilities affects health outcomes. While Carrillo and Feres (2019) show that an increase in the total number of doctors in rural Brazil had no effect on infant mortality, Okeke (2023) finds that posting an additional doctor but not a mid-level provider lowers infant mortality in Nigeria. Our findings expand this research by showing how mid-level providers can play an important role in the large-scale provision of services related to chronic diseases, where concerns about low healthcare quality might be less binding.[7]

Lastly, our results speak to an increasing literature that studies the interactions between the public and private sectors (Dinerstein and Smith, 2021; Dinerstein et al., 2023; Jiménez-Hernández and Seira, 2021; Atal et al., 2022; Andrabi et al., 2023). Previous work documents low levels of quality of public and private providers in developing countries (Das et al., 2008, 2016) and shows how training and regulation interventions can improve private sector quality (Das et al., 2016; Bedoya et al., 2023). Our findings contribute to the debate on the role of patient demand and provider financial incentives (Currie et al., 2014; Lopez et al., 2022) by providing direct evidence that local market power leads private providers to underinvest in quality.

The rest of this paper proceeds as follows. Section 2 discusses the institutional context. Section 3 gives an overview of the data and describes our empirical strategy. Section 4 presents our main results. Section 5 discusses mechanisms. Section 6 conducts the cost-

[6] We further relate to a growing literature on how to increase early diagnosis and treatment of patients with chronic diseases in developing countries (Cohen and Saran, 2018; Bai et al., 2021; Bronsoler et al., 2021). Our results are connected to previous research that shows how improving access to preventive care can have large health effects (Miguel and Kremer, 2004; Haushofer et al., 2021).

[7] Previous work also examines the effects of lower-skilled community health workers and social entrepreneurs on maternal and child health outcomes (Okwundu et al., 2013; Björkman et al., 2019). More broadly, our study relates to recent work that examines the effect of labor inputs in the public sector (Ganimian et al., 2021).

effectiveness analysis. Section 7 concludes.

2 Background

We begin by describing the health situation and the organization of the healthcare sector in rural India. We then discuss the details of the Health and Wellness Center reform.

2.1 Health and Healthcare in Rural India

Our study focuses on improvements to subcenters, the lowest level of public primary healthcare in rural India. Before the Health and Wellness Center reform, a typical subcenter was staffed by one *auxiliary nurse midwife* (ANMs) with a two-year diploma and three community health workers, also known as *accredited social health activists* (ASHAs). The median subcenter covers a population of 2,500 people from two villages. ANMs usually work from 9am to 3pm between Mondays and Saturdays and prescribe and dispense a limited number of medicines. They primarily focus on maternal and child care, spanning family planning services, prenatal and postnatal care checkups, and child immunization camps. However, as additional services were assigned to them over time, ANMs evolved into multipurpose healthcare workers who are also supposed to provide basic outpatient care, screen patients for chronic disease, and implement national health programs (Pyone et al., 2019). This leaves many ANMs overburdened: in our baseline survey, 69% of ANMs say that too much work is allocated to them and 57% say that they do not have sufficient time to complete their work. Since the ANMs perform most of their activities in the field, the physical subcenter building is rarely staffed. Only 42% of facilities in the control group were open during unannounced visits in our sample area. Similar patterns were also found in other studies (Singh et al., 2018).

Patients that the ANMs cannot treat are referred to *primary health centers* (PHCs), the next level up in the public primary healthcare system. Their staff usually consist of a physician, a pharmacist, and a nurse. The median clinic is linked to five subcenters. Public clinics are located in larger towns and the average distance between a clinic and a subcenter is 7 kilometers. All patients who are suspected to have hypertension and diabetes also need to visit the public clinic for official confirmation. Many chronic patients also have to visit the public clinic for their routine medicine since not all subcenters have the necessary medicine in stock.[8] Healthcare services and medicines at subcenters and public clinics are free for all patients in Rajasthan.

Private healthcare providers also play an essential role. Fifty-eight percent of subcenters have at least one private provider in the catchment area. Most of these providers have limited medical qualifications. In our baseline provider survey, 69% of them have less than a bachelor's degree. Their business model is the prescription and distribution of medicines with a markup. Many private providers violate legal prohibitions since they do not have the necessary medical degrees to practice, but support from the local community and limited enforcement capacity make it difficult to shut down these providers. Acknowledging these constraints, previous research has proposed to regulate the private sector instead by improving public facilities (McPake and Hanson, 2016). This approach, called "regulation by competition", assumes that the public sector can create competitive pressure to incentivize private providers to increase their quality and reduce their prices. Consistent with this argument, our surveys suggest that private providers have local market power, which could lead them to underinvest in quality. Forty-three percent of them are the only private provider in the catchment area, and their average profit margin is 39%.

Overall, healthcare quality is low in the public and private sectors. Previous studies find that less than half of the patients are correctly managed (Banerjee et al., 2023). Referrals to higher-level providers are rare, and providers over- and underprescribe antibiotics (Das et al., 2016; Mohanan et al., 2015). Lack of access to healthcare also remains a problem. Twenty percent of deceased patients in rural India did not receive medical attention before their death in 2017, according to the National Sample Survey.

The elderly are especially vulnerable. Multiple studies document that elderly neglect and abuse are common (Singh, 2014; Anand, 2016). Elderly patients are often constrained in their mobility and resources and are thus more reliant on the public sector. Data from the second wave of the Indian Human Development Survey shows that the elderly are 33% more likely to have visited a public provider when sick than children younger than 18 years. The

[8] In our survey area, 24% of subcenters had the routine medicine for hypertension (Amlodopine), and 33% of subcenters had the routine medicine for diabetes (Metformin) in stock.

elderly are also more likely to suffer from chronic diseases. According to the National Family Health Survey 5 (2019–2021), 46% of the elderly in rural India suffer from hypertension relative to 19% of adults under the age of 56 years.[9] The main problem among chronic disease patients is a lack of awareness of their condition since many chronic diseases do not come with obvious symptoms (Figure 1). Among elderly patients with high blood pressure, only 46% were ever diagnosed with the condition.[10] Conditional on diagnosis, 71% report currently taking medicine, and 43% had their blood pressure under control at the time of the survey. Awareness rates are even lower among the poorest households, where only 33% know that they suffer from high blood pressure.

2.2 The Health and Wellness Center Reform

The Government of India announced the Health and Wellness Center reform in September 2018 as one of two components of the Ayushman Bharat initiative. The other component is the expansion of public health insurance through the Pradhan Mantri Jan Arogya Yojana (PMJAY) scheme.[11] The Health and Wellness Center reform aims to improve access to public healthcare in rural areas and to avoid overutilization of higher-level facilities by strengthening the provision of public primary healthcare and converting 150,000 subcenters and public clinics to Health and Wellness Centers. The upgrades were "envisaged to deliver expanded range services that go beyond maternal and child health care services to include care for non-communicable diseases" (MHFW, 2023).[12]

The key component of the Health and Wellness Center Reform was the creation of a new cadre of mid-level health providers, known as *community health officers* (CHOs). CHOs are required to have either a three-year degree in general nursing and midwifery or a four-year bachelor's degree in nursing. They further need to complete a six-month bridge course

[9] Hypertension rates among the elderly are slightly higher in urban areas (50%).

[10] Panel B in Figure 1 shows similar gaps in awareness for diabetes.

[11] The Government of Rajasthan agreed to implement the PMJAY scheme in June 2019. A separate health insurance scheme under the name of Chiranjeevi Yojana was launched in May 2021.

[12] The reform was also supposed to increase the set of services available at subcenters. The new services include oral and dental care, eye care, elderly and palliative care, ear, nose, and throat care, mental health care, and the organization of Wellness and Yoga sessions. However, many of these services were not provided frequently during our study period due to insufficient awareness and limited availability of necessary equipment and medicines. We consider these additional services to be part of the strengthening of basic outpatient care.

upon being hired. The primary role of CHOs is to provide basic adult outpatient care and screening for chronic diseases at the subcenter level. The screening for chronic diseases is done through outreach camps and by screening patients who visit the subcenters during a routine medical consultation. Once posted, a CHO is the designated team leader of the health worker team at the subcenter. In our sample, the average age of newly hired CHOs is 28 years, and 64% are male. They are paid a fixed monthly salary of INR 25,000 ($\approx$ USD 300) plus INR 15,000 ($\approx$ USD 180) in performance-based incentives.[13]

Prior to the posting of CHOs, nominated subcenters were first converted to Health and Wellness Centers. Such conversions only involved minor improvements to infrastructure and did not impact the supply of medicine available at a given subcenter.[14] Subdistrict officials had to propose a fixed number of subcenters for conversion annually between 2018 and 2022. The minimum criterion for conversion was that the government must own the subcenter building. In some years, priority was further given to subcenters with electricity, running water, and good physical condition.

Existing correlational evidence suggests that the Health and Wellness Center reform led to higher levels of patient satisfaction (NHSRC, 2022). Additionally, in a pilot study conducted prior to the Health and Wellness reform, Muraleedharan et al. (2018) show that adding a second ANM to subcenters increases public healthcare utilization and decreases medical spending in a before-after analysis. To our knowledge, ours is the first study to estimate the causal effect of adding CHOs to subcenters on healthcare provision and health outcomes.

While the Health and Wellness Center reform was launched by the central government, the implementation was done at the state level. We study the effect of the CHO postings in Rajasthan, the seventh most populous state in India. Rajasthan is one of the poorest states in the country, but it has heavily invested in strengthening its healthcare system in the past

[13] The performance-based incentives cover a list of 15 service-based indicators at the subcenter level. ANMs and community health workers also receive smaller incentive payments. See Appendix Table A1 for details.

[14] The physical conversion of subcenters mostly consisted of the construction of another examination room and the painting of the walls in a bright yellow color for branding purposes. In our survey, 74% of ANMs said that a single additional room was built as part of the reform. Changes in electricity (2%), running water (3%), or equipment (2%) were rare. The reform was also supposed to increase the set of medicines available at the subcenters, but these changes had not yet been implemented during our analysis period.

years.[15]

3 Data and Research Design

In this section, we first describe our data sources and primary outcome variables. We then discuss our empirical strategy.

3.1 Data

We combine large-scale administrative data on the universe of public primary healthcare facilities in Rajasthan with primary survey data on 193 subcenters in Udaipur district. Appendix Figure A1 shows the timing of the different surveys. We start by describing the administrative data.

3.1.1 Administrative Data

We obtained the list of eligible subcenters and the assignments of CHOs from the Health and Wellness Center Portal. The portal has information on the date the subcenter was converted, the total population in the catchment area, and details on CHO characteristics, including their gender and posting date.[16] We also have information on the merit-based ranking of 88% of the CHOs from the government website based on a screening exam they took when they applied for the positions.

Our primary outcomes come from the Pregnancy, Child Tracking and Health Services Management System (PCTS) portal. The system contains aggregate information on healthcare services and deaths at the facility-month level. For outpatient care and chronic disease screenings, we examine the number of total patient visits as well as the number of hypertension and diabetes patient visits. The number of hypertension patient visits consists of all previously and newly diagnosed patients with high blood pressure who visited the subcenter that month (similarly for diabetes patients). The portal also contains information on the number of deaths across five age categories: infant deaths (<1 year), child deaths

[15] Rajasthan ranked 27th out of 33 states in 2019–20 in terms of GDP per capita. In 2020–21, the state allocated 7.1% of the government budget to healthcare, whereas other states spent, on average, 5.3%.

[16] The portal also contains detailed data on the number of patients screened for and diagnosed with chronic diseases. However, while most ANMs entered information into the portal before March 2022, many ANMs in control subcenters stopped doing so after March 2022, as CHOs in treatment subcenters took over the reporting responsibilities for this portal.

(1–4 years), adolescent deaths (5–14 years), adult deaths (15–55 years), and elderly deaths (56+ years). Deaths are separately reported across 19 different causes of death. We follow the public health literature and aggregate the different causes into four groups: chronic, acute, accident, and unknown-cause deaths. The ANMs report information on all deaths of residents in the catchment area, even if the death occurred somewhere else (e.g., at a district hospital). ANMs classify deaths based on hospital discharge sheets and conversations with household members of the deceased person. The majority of deaths (57%) are classified as deaths from unknown causes. The ANM continues to be the person who fills out the PCTS information even after CHOs are posted, and therefore, any differences in indicators cannot be attributed to a change in the reporting person. The mortality indicators are also not used for performance-based incentives. We further use the PCTS portal to get data on seven maternal and child healthcare indicators and the number of children with low birthweight.[17]

We obtain information on catchment area characteristics from the 2011 Population Census and the 2011 Socio Economic and Caste Census (through the Socioeconomic High-Resolution Rural-Urban Geographic Platform for India (Asher et al., 2021)). The population census provides information on literacy rates, employment rates, and Scheduled Caste and Scheduled Tribe population shares. The Socio Economic and Caste Census has information on land ownership rates, imputed consumption levels, and population shares by age group. We merge the census data with the facility-level data based on a linking file in the PCTS data that contains the 2011 census codes for all villages in the catchment area of a subcenter.[18] We generate indicators at the catchment area level using population-weighted averages across villages. We calculate the distance between subcenters and public clinics based on the village centroids in the census shape files.

We further obtained access to the Community Health Integrated Platform (CHIP), an annual healthcare household census of Rajasthan that Khushi Baby, a local NGO, developed, and that is collected through the community healthcare (ASHA) workers at subcenters. For

[17] We use the seven indicators to generate a maternal and child health services index. The seven service indicators are the number of registered pregnant women, the number of pregnant women with at least 4 prenatal care visits, the number of pregnant women that received 360 calcium tablets, the number of pregnant women that received their first tetanus shots, the number of women getting a postpartum check-up seven days after delivery, the number of fully vaccinated children (aged 9–11 months), and the number of children (age 12–59 months) that received Albendazole tablets.

[18] The linking file has the census codes for 90% of the catchment area villages.

the second round of the census, we were able to add questions on the healthcare provider choices for all household members. While the second survey round is still ongoing, we already have information on the healthcare provider choices of 11,683 household members who reported suffering from at least one symptom in the last 30 days.

3.1.2 Survey Data

We supplement our analysis of administrative data with two rounds of primary survey data on ANMs, CHOs, private providers, and households across 193 subcenters in four subdistricts in Udaipur district. In our ANM and CHO surveys, we obtained information on the personal details of each provider, the availability of medicine and infrastructure, and medical knowledge through two vignettes (child dysentery and adult asthma). At endline, the survey also included a time-use module about the activities of the ANMs and the CHOs in the last seven days.

We mapped all private providers in the catchment area of the subcenter at baseline and endline by surveying ANMs and two local shopkeepers. Once the mapping was complete, we attempted to survey each of the private providers. The survey collected information on the personal details of each provider, the number of coworkers, the availability of medicine and infrastructure, medical knowledge through two vignettes (child dysentery and adult asthma), the number of patients in the last 30 days, the share of patients who received antibiotics and injections, average fees, and participation in training workshops.

Among subcenters that had at least one private provider in the catchment area at baseline, we further conducted a phone survey with 529 households.[19] We obtained contact details through the list of registered pregnancies in the government portal. To be included in our sample, the household needed to have at least one registered pregnancy in the last five years.[20] The household survey collected information on healthcare symptoms, utilization, and spending patterns for all household members.

At endline, we further visited each sample subcenter without prior announcement for a

[19]Households that we could not reach over the phone at endline we also attempted to survey in person. This helped us to increase the survey completion rate at endline from 54% to 90%. The phone and in-person completion rates do not differ by treatment.

[20]According to the National Family Health Survey 5, 94% of pregnancies were registered in India in 2019–2021.

full day to collect information on facility opening rates. During these visits, we conducted exit surveys with all patients who visited the subcenter on that day to collect information on patient satisfaction and other measures of provider quality.

Appendix Table A2 shows that we obtained similar baseline and endline completion rates for all surveys across the treatment and control groups. We surveyed 95% of ANMs at baseline and 99% of ANMs at endline. The main reason for noncompletion is that the ANM was on temporary leave. We managed to conduct a baseline survey with 71% of the private providers we mapped in the catchment area. The main reasons for noncompletion were temporary closures and refusals. Out of the private providers still operational at the point of the endline survey, we managed to resurvey 88%. Among the private providers we surveyed at endline, we conducted a second follow-up survey to get repeat measures of the main outcomes and obtain additional information. For the household phone survey, we managed to reach 26% at baseline. Incorrect phone numbers were the main reason for noncompletion. Out of the households that completed the baseline survey, we managed to reach 90% again at endline.

3.2 Empirical Strategy

Our empirical strategy exploits where the first batch of CHOs in Rajasthan was posted. We next describe how the assignment decisions were made.

3.2.1 Reform Rollout in Rajasthan

The first batch of CHOs was assigned to subcenters at the end of March 2022.[21] At this point, 6,419 CHOs had been hired and passed the final exam.[22] The government then had to decide to which of the 10,016 converted subcenters the new providers would be posted. The posting decisions were implemented in two stages. In the first stage, CHOs were asked to rank districts according to their preferences. Assignments were then made based on their exam scores. In the second step, *chief medical and health officers*, the leading health officials

[21] A second batch of 500 CHOs was posted in late December 2022. We include them in the control group throughout our analysis. This affects 14% of subcenters of our final control group sample

[22] As a reference point, around 9,015 nurses with the relevant degree graduate from Rajasthan every year. In our survey data, we find that most of the hired CHOs say that they would have otherwise worked in the public or private sector in urban areas. We should thus think of the reform as the creation of new public sector jobs in rural areas.

at the district level, were asked to do the assignments within districts. All of the 33 Chief Medical and Health Officers in Rajasthan were requested to visit the state headquarters in Jaipur for a day to do the assignments. On that day, they received a list of the CHOs that were assigned to their district. The only information in that list was the names of the CHOs and their residential addresses. The second list included a list of all subcenters in the district that had been converted to Health and Wellness Centers. The list contained the names of the subdistrict and the subcenter. The only instructions given to the officials were to place the CHOs close to their homes. They were asked to finish the task by the end of that day.

We conducted qualitative interviews with two officials who were involved in the process to understand how the assignments were made in practice. We were told that the district officials had tried to place CHOs within the area of their residence but had not accounted for the exact distance between each subcenter and a CHO's home. Since each district official had to allocate 195 CHOs across 304 subcenters on average, it would have been impractical to find the nearest subcenter for each of them. Whenever CHOs resided in the district headquarters or came from outside of the district, they were assigned across the entire district with the aim of achieving balance across subdistricts.[23]

Data from an extended survey that we conducted with 243 Community Health Officers in Udaipur corroborate this process. Ninety-eight percent of the CHOs said that they were not involved in assignment decisions within the district. Figure 2 visualizes the assignment process through a map of subdistricts in Udaipur district. The bubbles in Panel A correspond to the previous residence of the CHOs. Forty-three percent of the CHOs came from the district headquarters and 12% came from outside the district. Panel B shows the locations of converted subcenters. To shed light on how the assignments were made, we present three examples in Panels C, D, and E. In Panel C, we observe that the five CHOs who previously resided in Kherwara subdistrict were all assigned to a subcenter near their previous residence in the southwestern part of Udaipur district. However, when comparing the assignments with the list of available subcenters in Panel B, we also see that the CHOs were not necessarily assigned to the subcenter that was located closest to their home. Instead, district officials

[23]District headquarters are located in urban centers and so were not served by the Health and Wellness reform.

relied on rules of thumb to make the assignments. Panels D and E further show that CHOs from the district headquarters or from other districts were assigned across all subdistricts. Finally, Panel F shows the final assignment outcomes in all of Udaipur district. We highlight that many subcenters in close vicinity differ in their treatment status, consistent with the idea that many assignments were based on ad-hoc decisions.

3.2.2 Matching and Estimation

Since assignments were based on CHO's preferences for districts and the location of their previous residence, subcenters that received a CHO are more likely to be located in less remote areas, making the parallel trend assumption less likely to hold in the unconditional sample. We address this concern by computing weights for the control group to match subcenters with and without a CHO based on our knowledge of the assignment rule. In particular, we use district fixed effects interacted with linear and squared terms of a facility's distance to the district and subdistrict headquarters to estimate propensity scores.[24] We then follow Abadie (2005) and use inverse probability weighting to adjust the control group. The intuition is that control group subcenters that were less likely to have been assigned a CHO receive less weight. By contrast, control group subcenters that were more likely to have been assigned a CHO receive more weight, making the control group more similar to the treatment group.

In our preferred specification, we exclude districts in which more than 90% of subcenters received a CHO to avoid large weights. We also exclude the subdistrict nearest to the district headquarters in each district since they were systematically more likely to receive treatment as most CHOs previously lived in the district headquarters.[25] Following the matching literature, we further implement common support restrictions by excluding observations within the top or bottom 2.5 percent of either the control or treatment group propensity score distribution in each district (Appendix Figure A2). In practice, this excludes the most and least remote subcenters from the sample. We show that our results are robust to alternative

[24]We do not use the distance to the nearest physician-staffed public clinic since the name of the associated clinic was not included in the list of converted subcenters that was given to the district officials during the assignment process. The results are similar if we also use the distance to the public clinic in the estimation of the propensity score.

[25]Within a district, subcenters in the subdistrict nearest to the district headquarters are 15% (p-value = 0.000) more likely to receive a CHO than subcenters in other subdistricts.

sample restrictions and matching strategies, including entropy balancing (Hainmueller, 2012) or estimating propensity scores based on LASSO regressions.

Table 1 compares baseline covariates across treatment and control subcenters in the unconditional and matched samples. Columns 1–4 show that treatment subcenters are less rural, more literate, and cover a larger population than control subcenters. However, once we reweight the control group based on the geographical information, we also achieve balance among most non-targeted subcenter characteristics (columns 5–8). Differences in the scheduled caste share and the literacy rate remain significant but are small in magnitude.

We also note that any systematic variation in *levels* does not undermine the validity of the empirical design. Our primary identifying assumption is that in the absence of the new CHOs, control and treatment subcenters would have followed the same trends in the outcomes of interest. This assumption would only be violated if treatment and control areas had differential trends in time-varying determinants of outcomes. For example, richer and less remote areas might have experienced a stronger decline in mortality outcomes during our sample period, even in the absence of the treatment. We thus focus our analysis on the reweighted sample that looks more similar on observables in the preperiod. More broadly, we also use our empirical specification to check for differential pre-trends. The argument is that any changes between treatment and control subcenters in the post period are likely to be caused by the treatment if both types of subcenters followed similar trends before the CHOs were posted. As we discuss below, we do not find evidence for pre-trends that would undermine our results.

We aggregate outcomes at the quarterly level since monthly data on deaths is very noisy. For subcenter i in quarter t, we estimate:

$$y_{it} = \alpha + \sum_{k=-2}^{k=-4} \beta^k_{pre} 1[D_{bt} = k] \times Treat_i + \sum_{k=0}^{k=3} \beta^k_{post} 1[D_{bt} = k] \times Treat_i + \delta_i + \eta_t + \epsilon_{it} \quad (1)$$

where $1[D_{bt} = k]$ is an indicator for k quarters between quarter t and the second quarter in 2022, the quarter the CHOs were posted at the subcenters.[26] δ_i are subcenter fixed

[26] The assignment decisions were made at the end of March 2022, and the CHO started to work in the facilities in April 2022.

effects, which absorb any time-invariant factors like persistent facility characteristics such as infrastructure and local risks of diseases. η_i are quarter fixed effects that absorb common time trends such as seasonal variation in diseases. We cluster our standard errors at the subcenter level to account for serial correlation. To test for pre-trends, we report p-values for the null hypothesis that all preperiod coefficients are statistically equal to zero.

We also run the standard difference-in-differences regression to analyze pooled treatment effects:

$$y_{it} = \alpha + \beta_1 Treat_i \times Post_t + \beta_2 Treat_i + \beta_3 Post_t + \delta_i + \eta_t + \epsilon_{it} \tag{2}$$

As a benchmark for the magnitude of the effects, we report the counterfactual treatment group means in the post periods by subtracting the treatment coefficient from the observed treatment group mean in the post periods. We top-code all continuous outcomes at the 99% level to reduce the influence of outliers.[27]

We replicate a similar empirical strategy for the analysis of our survey data. To maximize sample size, we include 71 subcenters that had a government-owned building but had not been converted to a Health and Wellness Center by March 2022. These subcenters were not eligible to receive a CHO when the posting decisions were made, but they could have been eligible had the subdistrict officials chosen these subcenters for conversion first. We adjust the estimation of the propensity scores to be consistent with the criteria that were used to select facilities for conversion.[28] Appendix Table A3 shows that the reweighted survey sample is balanced for almost all nontargeted characteristics. The only exception is the maternal and child health services index, which was 0.26 standard deviations higher in treatment areas at baseline.

4 Results

We start by examining the effects of CHOs on the provision of healthcare services and health outcomes. We then check the robustness of the results and discuss additional findings.

[27]We show robustness to alternative top-coding strategies in Appendix Table A9.

[28]In addition to the distance to the district and subdistrict headquarters, we also include subdistrict fixed effects and baseline survey information on the condition of the subcenter building and the availability of electricity and running water in the estimation of the propensity scores for the survey sample.

4.1 Effects on Service Provision

The top left panel in Figure 3 shows the effects of the CHOs on patient visits over time.[29] While treatment and control subcenters followed similar trends prior to the reform, we observe a substantial increase in the number of patient visits once the CHOs were posted to treatment subcenters. In Column (1) of Table 2, we show that the number of patient visits in a quarter increases on average by 215 visits (p-value < 0.001). Relative to a counterfactual treatment group mean of 317 patients per month, this represents an increase of 68%.

We also find substantial increases in the number of patients diagnosed with chronic illnesses that visit the subcenter. The number of hypertension patient visits increases by 67% (p-value < 0.001), and the number of diabetes patients increases by 62% (p-value < 0.001). The preperiod means show that ANMs were already seeing four hypertension and three diabetes patients per quarter on average. Screening for chronic diseases is thus not a completely new service provided at the subcenter level. Instead, the posting of the CHOs increases capacity by posting to subcenters an additional provider who is directly tasked with providing services to chronic disease patients.

As mentioned in Section 3.1, these outcomes include newly and previously diagnosed patients. While the increase in patients diagnosed with hypertension and diabetes could theoretically also be driven by an increase in the prevalence of chronic diseases, the low awareness rates in the population make it much more likely that the increase in chronic disease patients is due to higher screening rates. We use data from the Health and Wellness Center portal that is only available for treatment subcenters to get a better understanding of how CHOs affect chronic patients. Appendix Figure A4 shows a clear increase in the number of hypertension and diabetes patients who are screened, newly diagnosed, or treated after the posting of the CHOs.

We also examine the effect of CHOs on an index of seven maternal and child health services. As discussed previously, the direction of the treatment effect is ambiguous ex ante. Even if CHOs only had limited involvement in maternal and child health services, their presence could still have freed up additional capacity for the ANMs. However, an increased

[29] Appendix Figure A3 shows the trends in our main outcomes separately for treatment and control subcenters.

focus on chronic diseases and basic outpatient care could have also led to a neglect of existing services. Overall, we do not observe substantial changes in the provision of maternal and child health services. Appendix Table A5 shows that we also find no improvements when we analyze each index component individually.

4.2 Effects on Health Outcomes

We use elderly deaths, defined as deaths of adults aged 56 or older, as our main health outcome since the health outcomes of the elderly are likely to be more sensitive to better outpatient care and screening for chronic diseases than the health outcomes of other age groups (Bailey and Goodman-Bacon, 2015). Our preferred outcome specification examines a binary version of whether a subcenter reports any elderly death in a particular quarter as well as the inverse hyperbolic sine of the elderly mortality rate.[30,31] We also report effects on the number of elderly deaths and elderly mortality rates in levels in Columns (2) and (5) in Table 3. The top-level panel in Figure 4 shows the corresponding event-study graph. We find that the coefficients for the first three pretreatment quarters are neither individually nor jointly significant (p-value = 0.163). However, once the CHOs are posted, we observe a significant decline in the likelihood that any death occurred in the catchment area in a particular quarter.[32] Overall, we find that the CHOs decrease the probability of any elderly death by 3.1 percentage points (p-value = 0.005, Table 3, Column (1)) and the total number of deaths by 12% (p-value = 0.023, Column (2)). The results are similar for elderly mortality rates (Columns (3)–(4)). Appendix Table A4 further breaks down the outcome into different causes of death. We observe that the aforementioned declines in deaths are completely driven by a decline in deaths from unknown causes. We think that this is consistent with higher

[30] The benefit of the binary outcome is that it is less noisy than examining mortality rates. On average, 25% of subcenters report at least one elderly death in a given quarter. Conditional on reporting any death, 36% report one death, 24% report two deaths, and 15% report three deaths.

[31] The elderly mortality rate is defined as the number of elderly deaths per 1,000 elderly individuals. We calculate the number of elderly individuals in each catchment area by multiplying the total population in the catchment area by the average elderly population share (8.87%) in the Socio Economic Caste Census in 2011. We find similar results if we use village-level elderly population shares from 2011, with the exception that the treatment effect on elderly mortality rates in levels becomes noisier.

[32] The effect of elderly deaths seems to fade out three quarters after the CHO posting, but the confidence intervals still cover substantial declines in mortality. Besides the noise in the outcome, such a decline in treatment effects would be consistent with the existence of a new equilibrium in which life expectancy is increased by one year. In addition, the treatment effects could be weakened in the last quarter since 14% of control group subcenters had also received a CHO at this point.

screening rates for chronic diseases since a deceased person first needed to be diagnosed with a chronic disease to fall into this category.

Consistent with the lack of effects on maternal and child health indicators, we do not observe any changes in infant deaths (Columns (5)–(8)).[33] While policymakers may have hoped that the additional capacity at the subcenters would reduce infant mortality, it is still reassuring to find that the new focus of subcenters on chronic disease screening and basic outpatient care did not come at the expense of maternal and child health outcomes. The results are also related to Okeke (2023) who finds that posting another mid-level provider in Nigeria did not affect infant mortality, whereas posting a physician did. His study argues that this shows that quality is the binding constraint for further improvements to maternal and child health. Our findings are consistent with this interpretation, but also show how access to outpatient care and chronic disease screening can be a binding constraint for the elderly. Appendix Table A6 shows that we also find no treatment effects on the mortality outcomes for other age groups.

A potential concern is that differences in reporting could explain our results. However, as mentioned in Section 3.1, the ANM remains the person who fills out the information forms for the PCTS portal and then gives them to the data entry operators at the public clinic to be digitized. In our time-use module, we also do not find that ANMs at treatment subcenters spent more days on administrative and reporting tasks. Better reporting would likely also go against us finding declines in mortality since an increase in the quality of reporting should increase the reported number of deaths in treatment areas. A general increase in the quality of reporting should further show up in other outcomes as well, including maternal and child health indicators.

We further supplement our analysis of administrative data with our own household survey data from 193 catchment areas in Udaipur district. The survey allows us to address reporting concerns and examine the effect of CHOs on additional health outcomes not observed in the administrative data. Table 4 shows that we see no effects on medical spending and the likelihood of having suffered from any symptom in the last 30. However, consistent with

[33] We also assessed the effects on the number of newborns with low birthweight and found no differences either (Column (8), Appendix Table A5).

the decline in mortality, we observe a decline in hospitalizations by 1.7 percentage points (p-value = 0.030, Column (2)). This effect is driven by a decline in hospitalizations among elderly patients (Appendix Table A7).

4.3 Robustness

We implement various robustness checks for our results. We find similar treatment effects if we use alternative common support restrictions (Appendix Table A8) and top-coding strategies (Appendix Table A9). A potential concern is that the district officials also used additional information besides the geographical location of the subcenter to assign CHOs. Panel A in Appendix Table A10 estimates propensity scores using a LASSO regression based on all variables listed in Table 1 instead. Even if district officials only used geographical information, it is also possible that the functional form of the propensity score function is incorrectly specified. We address this concern by replicating our analysis with entropy balancing weights (Hainmueller, 2012). This method chooses the set of control group weights that minimally deviate from uniform weights while matching a specific set of moments between the treatment and control groups.[34] We find similar effects in both instances. As shown in Appendix Table A11, our results are also robust to including subcenter-specific linear time trends in the regression and to using the double-robust difference-in-differences estimator proposed by Sant'Anna and Zhao (2020).

Another concern relates to spillover effects. The average control subcenter is 6.6 kilometers away from the nearest treatment subcenter. In practice, we do not observe that any household members in our survey data ever visit a different subcenter besides the one in their catchment area. The likely reason is that patients prefer to go directly to the public clinic in the nearest town, which is, on average, 7.3 kilometers away. We further note that the existence of spillover effects would likely lead us to underestimate the treatment effects since control group households would also experience the benefits of improved access to health care.

Finally, we conduct an alternative empirical strategy in which we match each treatment

[34] Following our information on the assignment rules, we use the average distance to the district and subdistrict headquarters and the average share of subcenters in each district as our matching moments.

subcenter to the closest control group subcenter.[35] The intuition is that subcenters in the same geographical vicinity should follow the same trends in health outcomes in the absence of the CHO postings. Appendix Table A12 shows that our main results become noisier but remain significant at the 10% level if we use this approach instead.

4.4 Discussion

An important question is whether the size of the effects is reasonable. One way to address this concern is to look at previous studies that examined the effect of improved public healthcare on short-run health outcomes. Past research has shown that adding a physician to a public facility or improving community monitoring can reduce infant and child mortality by 20%–33% within one year of an intervention (Björkman and Svensson, 2009; Okeke, 2023). Studies on infant and child mortality, however, might be less informative since the health outcomes of new infants are likely to be more sensitive to targeted improvements to public healthcare than the health outcomes of the elderly. While there is less evidence on the short-run effects of public health intervention on adult mortality, existing work also documents the potential for substantial improvements. Bailey and Goodman-Bacon (2015) focus on the long-run effects of community health centers in the US, but their event study graphs also suggest sharp declines in adult mortality within the first year of treatment. Besides improvements to primary care, previous work has shown how healthcare insurance can lead to a decline in adult mortality. Gruber et al. (2023) report that a healthcare insurance expansion in China decreased adult mortality by 12%. Their event study graphs suggest that some of these effects already occurred within the first year. Sood et al. (2014) further find that healthcare insurance in India reduced mortality from conditions covered by the scheme by 64% within two years.

The mortality effects of CHOs on elderly mortality could either be driven by higher screening rates for chronic diseases or better management of outpatient care patients. Our data does not allow us to distinguish between both channels perfectly. In practice, they are also closely linked to each other since treatment group patients often get screened when they visit the subcenters for other symptoms. Existing research on the effect of screening campaigns

[35] We implement matching with replacement, allowing each treatment subcenter to be matched to more than one control group subcenter.

on mortality focuses on longer-run outcomes. Among studies that find short-run effects, Lin et al. (2004) show that a hypertension mass campaign led to a substantial decline in stroke mortality within a year in Taiwan, and Hickey et al. (2021) find that patient-centered hypertension care reduced all-cause mortality among adults with uncontrolled hypertension by 21% within three years in rural Kenya and Uganda.

To understand how much of the decline in elderly mortality is due to higher screening rates, we conduct two back-of-the-envelope calculations. One approach is to use the treatment effect from Hickey et al. (2021)[36] and multiply it by the share of elderly deaths caused by hypertension in India according to the Global Burden of Disease Study (19%). In that case, we could expect a decline in elderly mortality by 4% from better hypertension control alone. This could go up to 7% if we expect similar treatment effects for diabetes patients. In a more conservative approach, we combine our treatment effects on the number of newly diagnosed hypertension and diabetes patients with information on treatment adherence rates from NFHS-5 data and treatment efficacy information from the medical literature (Monami et al., 2021). The calculation suggests that higher hypertension and diabetes screening rates could explain a reduction in all-cause mortality by 3%. Overall, we thus predict that between 25%–58% of our observed effects are due to better screening for chronic diseases, while the rest of the effect is likely driven by access to better management of outpatient care patients.

So far, our results have only shown that we observe an increase in the number of hypertension and diabetes patients at treatment subcenters. It is possible that these patients would have otherwise been screened at other public facilities. To assess this concern, we use data on the number of patients diagnosed with and treated for hypertension and diabetes at physician-staffed public clinics. Since the official protocol requires that all newly diagnosed patients at subcenters visit the public clinics for confirmation, we would expect that the number of diagnosed patients would be higher at those public clinics that are located in areas where more subcenters received a CHO. We test this by splitting public clinics into two groups based on whether at least half of the (population-weighted) subcenters linked to the

[36]Hickey et al. (2021) compare a standard treatment to a patient-centered chronic care model for patients who suffered from uncontrolled hypertension at baseline. While their treatment arm is more intensive and their study examines a longer time horizon, even the control group in their study received some form of treatment.

clinic received a CHO in the spring of 2022. Appendix Table A13 shows that, consistent with higher overall diagnosis rates, public clinics with more treatment subcenters experienced an increase in the number of hypertension patients who were diagnosed and treated at public clinics.[37] While we cannot completely rule out that the patients would not have otherwise been diagnosed in the private sector, we find in our survey of 25 hypertension patients in our control group that 76% of them got diagnosed in the public sector. This suggests that public healthcare providers play a dominant role in screening patients, making it less likely that we only observe a shifting of patients from private to public providers.

We further use preliminary data from the second round of the Community Health Integrated Platform healthcare census in Rajasthan to examine how the CHOs affect overall healthcare utilization rates. Using information on provider choices for 11,683 household members who were sick in the last 30 days across Rajasthan, we find that the share of households who visited the subcenter increased from 29% to 51% in treatment areas (Figure 5). Reassuringly, the relative increase in SHC utilization by 76% is very similar to the increase in patients we observe in the administrative data. The figure further shows that most of the increased utilization of subcenters is due to a decrease in the share of patients who did not seek care when sick. These differences in the extensive margin further support the plausibility of our mortality results since they suggest that the CHOs postings were able to support patients who would have otherwise not sought healthcare.

We also assess how the treatment effects differ based on the distance to the physician-staffed public clinic. We note that the distance to the next-level primary healthcare facility can matter in multiple ways. On the one hand, CHOs that are closer to the public clinics can triage more easily, and their chronic patients will have better access to routine medicine. Subcenters closer to clinics are also easier to monitor. On the other hand, subcenters that are farther away from public clinics can benefit more from CHOs since households near these subcenters have less access to alternative healthcare providers. We split the subcenter sample

[37] As shown in column (1) in Appendix Table A13, we do not observe a change in overall patient visits to public clinics. While the CHOs could have reduced congestion at higher-level facilities, most clinics are not capacity-constrained. We surveyed the physicians at 39 public clinics at endline, and only four of them told us that they had reached their capacity in the last 30 days. According to self-reports, the average waiting time for patients is also only 6 minutes at public clinics. We observe no differences in self-reported waiting times or the number of minutes physicians spent with patients based on the share of linked subcenters that received a CHO in our cross-sectional analysis.

into terciles based on their distance to the public clinic in Appendix Table A14. We observe similar increases in the provision of healthcare services, but find suggestive evidence for a U-shaped relationship for the declines in elderly mortality. Mortality declines are the largest for the most remote subcenters (Panel C). We also observe noisy declines in mortality for the subcenters that are closest to public clinics (Panel A), but no changes for subcenters in the middle tercile (Panel B). While the confidence intervals are large once we subset our sample, we can use these point estimates to assess how much elderly mortality could have declined had the government prioritized subcenters farthest from public clinics when allocating the first cohort of CHOs. In that case, we predict that the overall decline in elderly mortality could have increased from 12% to 16%.

The substantial declines in mortality for the most remote subcenters also indicate that CHOs can be effective even if monitoring is limited, suggesting that the findings also apply to settings with less state capacity. A related question is whether CHOs can also still improve health outcomes when facilities have insufficient infrastructure. Since we do not have data on subcenter infrastructure for the full sample, we instead use our survey sample to compare the effects of CHOs on health outcomes at subcenters that did and did not have electricity at baseline. As shown in Appendix Table A15, the decline in elderly mortality and hospitalizations is completely driven by subcenters that had electricity.[38] These results indicate potential complementarities between labor inputs and physical infrastructure, suggesting that additional investments along with the posting of mid-level providers might be necessary to replicate the results in more resource-poor settings.

5 Mechanism

We rely on our primary survey data to shed light on the mechanisms underlying our results. Appendix Table A16 shows the two margins that are affected by the treatment. The posting of the CHOs not only doubles the number of workers at subcenters (Column (1)) but also increases the highest medical qualification available at the subcenter level (Column (2)). We thus separately assess how the reform affected the availability and quality of healthcare

[38]We consider electricity as a proxy for the broader infrastructure of the subcenter. We also find similar effects if we instead split the sample based on the physical condition of the facility.

services. As shown in Columns (3)–(6), we observe no differences for other characteristics, including the number of community health workers and the availability of equipment and medicines.

5.1 Healthcare Access

We start by analyzing how the CHOs increase access to care. Figure 6 presents the results from a time-use module that we conducted with ANMs and CHOs at endline. In this module, we asked them to report the activities they conducted on each of the past seven days. We find that the CHOs primarily increase the time spent on providing outpatient care and screening for chronic diseases. This is in line with findings from other studies (Brar et al., 2021).

We do not see differences in the time allocation of ANMs between treatment and control subcenters. We also do not find a change in the share of ANMs who report that they are overworked. Instead, ANMs told us that they appreciated the arrival of CHOs but that their workload in the provision of maternal and child health services had not changed much. The lack of differences in the ANM's time allocation and workload could explain why we do not observe treatment effects on maternal and child health indicators.

An important change of the reform was also that the opening hours of the subcenters became more reliable. Appendix Figure 7 shows the results from unannounced audit visits that we conducted at endline. We see that treatment subcenters are 64% more likely to be open at all on the day of the audit visit than control subcenters. Treatment subcenters are, on average, open for 2.8 more hours and see 51% more patients at the subcenter per day.[39]

The patient exit surveys also allow us to examine who are the marginal patients who visit treatment subcenters. When regressing patient characteristics on a treatment dummy, we find that patients at treatment subcenters are more likely to come from Scheduled Castes (Appendix Table A17), suggesting that the CHOs especially benefit disadvantaged communities. Treatment group patients surveyed on the day of the audit visits are also more likely to say that this is the first time that they ever visited the subcenter.

[39] While the relative increase in patient visits is consistent with our previous results, the total number of patients that we observe in the audit visits is much lower than the implied number of daily patient visits in the administrative data. A potential explanation for this pattern is that ANMs and CHOs also count patients that they treat while they are in the field.

5.2 Healthcare Quality

We further assess how the CHOs affect the provision of healthcare. Figure 8 plots the checklist completion rate for the two medical vignettes for different providers. As we would expect, we find that the knowledge of the new CHOs lies between the knowledge of ANMs and public clinic physicians. We can reject that the knowledge distributions of ANMs and CHOs are the same (p-value = 0.016).[40] We find no difference in the knowledge between treatment and control group SHCs. We also find that the private providers in the catchment areas have similar levels of medical knowledge as the existing ANMs. During our audit visits, we also conducted exit surveys with all patients who visited the subcenter on that day. Table 5 shows that patients at treatment subcenters report higher levels of satisfaction. Patients at treatment subcenters were also asked more questions, were more likely to have their blood pressure measured, and were more likely to be referred to the physician-staffed public clinic. These differences remain if we try to control for patient selection by controlling for symptom fixed effects or restricting the sample to patients who report having visited the subcenter before.

Is the change in access or quality driving the results? While our variation does not allow us to directly distinguish between both mechanisms, we take a step in that direction by analyzing whether the treatment effects vary based on the quality of the CHO. We use two proxies for provider quality: their merit-based exam score ranking and their checklist completion rate in the medical vignettes (the latter is only available at subcenters included in our survey sample).[41] The thought experiment of this exercise is that an alternative reform could have posted a second ANM to subcenters instead of a higher-qualified CHO.[42] As shown in the distributions of medical knowledge, CHOs perform better than ANMs on average, but there is substantial overlap. The top-third ANMs do approximately as well as the bottom-half CHOs. Appendix Table A18 shows that we cannot reject that the treatment effects are the same for low- and high-quality CHOs. The increase in the number of patient

[40] These differences are driven by the adult asthma vignette (Appendix Figure A5). We cannot reject that the knowledge distributions for ANMS and CHOs are the same for the child dysentery vignette, adding to the potential explanations for why we observe no treatment effects on maternal and child outcomes.

[41] Both measures are significantly correlated with patient satisfaction in the exit surveys.

[42] The state of Tamil Nadu implemented such a policy and posted a second ANM as part of the Health and Wellness Center reform instead (Muraleedharan et al., 2018).

visits is very similar in both groups. The decline in hospitalizations tends to be larger for higher-quality CHOs, but we do not have sufficient statistical power to detect significant differences. Overall, the lack of large differences is consistent with the idea that the effects are driven by increased access to basic services that do not require intensive medical knowledge, like the measurement of high blood pressure and the treatment of basic health symptoms.

5.3 Effects on Private Provider Quality

Finally, we also examine whether changes to private providers could contribute to the observed changes in health outcomes. A recent set of studies has documented the existence of such multiplier effects in education, where private schools react to increased competition from public schools by increasing their quality. (Andrabi et al., 2023; Dinerstein et al., 2023). However, other work has also shown that increased competition in healthcare markets could increase the adoption of potentially harmful practices that are demanded by patients, including the overuse of antibiotics and opioids (Bennett and Yin, 2019; Currie et al., 2023). More broadly, increased competition could also hurt some patients by leading to private provider exit (Dinerstein and Smith, 2021) or higher private sector prices through market segmentation (Atal et al., 2022).

We find no treatment effects on the total number of providers in the market (Column (1), Appendix Table A19). Instead, we thus focus on analyzing treatment effects on provider attributes in Table 6. While we do not observe any differences in the number of patients or prices (Columns (1)–(2)), we find that the posting of the CHOs increases the quality index of private providers by 0.2 standard deviations (p-value = 0.071, Column (3)). This effect is concentrated among providers that are located close to the subcenter (Panel B). The increase in quality is driven by an increase in the number of training workshops attended, the likelihood of currently being enrolled in a medical degree program, and the number of workers at the clinic (Table A20). We note that the effects are driven by quality characteristics that are very visible to patients, consistent with recent work on the importance of signaling in healthcare markets (Banerjee et al., 2023). We observe no differences in the share of patients who received antibiotics or injections, providing evidence against concerns that potentially harmful behavior could increase with competition (Columns (2)–(3), Appendix Table A19).

Overall, these results suggest that improvements in the private sector might have contributed to the observed changes in health outcomes. More broadly, our results further indicate that local market power seems to be one of the reasons for why the private sector in rural healthcare markets underinvests in quality.

5.4 Alternative Mechanisms

As mentioned in Section 2, the Health and Wellness Center reform was launched alongside an expansion of the health insurance scheme. In Rajasthan, the new insurance schemes were launched approximately one year before the CHOs were posted. It might still be possible that the main channel through which CHOs affect health outcomes is by encouraging patients to enroll in the new insurance scheme. We assess this channel through our household survey data and find no significant increase in the likelihood that the household is covered by healthcare insurance. Another channel that could matter is the availability of a male primary healthcare worker at subcenters. While all of the existing ANMs are female, 64% of the new CHOs are male. We thus repeat our heterogeneity analysis in Appendix Table A21. We find that male CHOs tend to lead to a slightly higher increase in patient visits, but we cannot rule out that the treatment effects are the same for the other outcomes.[43]

6 Cost-Benefit Analysis

We next assess the cost-effectiveness of posting CHOs to subcenters. For government costs, we consider increased salary and drug expenses. CHOs are paid USD 480 per month. Since medicine is provided for free at public facilities, we also account for higher public spending on medicines. We assume that the average medicine cost per patient visit is USD 0.24. When assessing government benefits, we account for future reductions in government spending due to decreased hospitalizations. We use estimates from Garg et al. (2022) who calculate that average public spending per hospitalization day is equal to USD 18.24.

For private benefits, we consider the decline in elderly mortality as well as decreased out-of-pocket spending for hospitalization and private sector visits. We follow Hendren

[43]Unfortunately, our data does not allow us to analyze gender-specific mortality rates. We have gender-disaggregated data on the number of patients for treatment subcenters from the Health and Wellness Center Portal. We find that, while male CHOs tend to increase the share of male patients visiting the subcenters, the relative differences are small in magnitude.

and Sprung-Keyser (2020) and use USD 100,000 as the value of a statistical life year. For hospitalization, we again use estimates from Garg et al. (2022) who calculate that average private spending per hospitalization is equal to USD 37.02.

Taken together, these results imply a marginal value of public funds of 51. In other words, the posting of the CHOs generates 51 dollars in private benefits for every government dollar spent. We also estimate the cost per life-year saved is equal to USD 3,069.[44] This corresponds to 1.3 times the GDP per capita in India. This is below the benchmark of the World Health Organization, which classifies interventions as cost-effective if they cost up to three times GDP per life-year saved (Patenaude et al., 2019).

7 Conclusion

As developing countries become richer and their populations grow older, they undergo an epidemiological transition that requires reforms to public healthcare. Policies that use mid-level providers to improve access to basic outpatient care and screening for chronic diseases can be low-hanging fruits to improve health outcomes. We exploit one of the world's largest expansions of public primary healthcare to show that adding mid-level providers to remote public facilities can lead to substantial improvements in the provision of public healthcare and to reductions in elderly mortality without deterioration in maternal and child health outcomes.

[44]Without accounting for the decrease in hospitalizations, the costs per life-year saved are equal to USD 16,649. By comparison, Bailey and Goodman-Bacon (2015) estimate that Community Health Centers in the US cost USD 68,580 per life-year saved (after deflating their estimates to 2022 dollars). Medicaid costs between USD 204,470 and 582,930 per life-year saved (Chay et al., 2012).

References

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The Review of Economic Studies 72*(1), 1–19.

Anand, A. (2016). Exploring the role of socioeconomic factors in abuse and neglect of elderly population in Maharashtra, India. *Journal of Geriatric Mental Health 3*(2), 150–157.

Andrabi, T., N. Bau, J. Das, N. Karachiwalla, and A. I. Khwaja (2023). Crowding in private quality: The equilibrium effects of public spending in education. Working Paper 30929, National Bureau of Economic Research.

Asher, S., T. Lunt, R. Matsuura, and P. Novosad (2021). Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in India using the shrug open data platform. *The World Bank Economic Review 35*(4).

Atal, J. P., J. I. Cuesta, F. González, and C. Otero (2022). The economics of the public option: Evidence from local pharmaceutical markets. Working Paper 30779, National Bureau of Economic Research.

Bai, L., B. Handel, E. Miguel, and G. Rao (2021). Self-control and demand for preventive health: Evidence from hypertension in India. *Review of Economics and Statistics 103*(5), 835–856.

Bailey, M. J. and A. Goodman-Bacon (2015). The War on Poverty's experiment in public medicine: Community health centers and the mortality of older Americans. *American Economic Review 105*(3), 1067–1104.

Banerjee, A., J. Das, J. Hammer, R. Hussam, and A. Mohpal (2023). The market for healthcare in low income countries. Working Paper.

Banerjee, A. V., E. Duflo, and R. Glennerster (2008). Putting a band-aid on a corpse: incentives for nurses in the Indian public health care system. *Journal of the European Economic Association 6*(2-3), 487–500.

Bedoya, G., J. Das, and A. Dolinger (2023). Randomized regulation: The impact of minimum quality standards on health markets. Working Paper 31203, National Bureau of Economic Research.

Bennett, D. and W. Yin (2019). The market for high-quality medicine: Retail chain entry and drug quality in India. *Review of Economics and Statistics 101*(1), 76–90.

Birje, S., A. D. Patil, K. R. Munne, V. Chavan, B. N. Joshi, A. Akula, N. Salvi, S. Nair, S. P. Valawalkar, D. Tandon, et al. (2022). Enablers & challenges of tribal women & health system for implementation of screening of non-communicable diseases & common cancers: A mixed-methods study in Palghar district of Maharashtra, India. *The Indian journal of medical research 156*(2), 319.

Björkman, M., A. Guariso, J. Svensson, and D. Yanagizawa-Drott (2019). Reducing child mortality in the last mile: Experimental evidence on community health promoters in Uganda. *American Economic Journal: Applied Economics 11*(3), 155–192.

Björkman, M. and J. Svensson (2009). Power to the people: evidence from a randomized field experiment on community-based monitoring in Uganda. *The Quarterly Journal of Economics 124*(2), 735–769.

Bloom, D. E., E. T. Cafiero-Fonseca, M. E. McGovern, K. Prettner, A. Stanciole, J. Weiss, S. Bakkila, and L. Rosenberg (2014). The macroeconomic impact of non-communicable diseases in China and India: Estimates, projections, and comparisons. *The Journal of the Economics of Ageing 4*, 100–111.

Brar, S., N. Purohit, S. Prinja, G. Singh, P. Bahuguna, and M. Kaur (2021). What and how much do the community health officers and auxiliary nurse midwives do in health and wellness centres in a block in Punjab? A time-motion study. *Indian Journal of Public Health 65*(3), 275–279.

Bronsoler, A., J. Gruber, and E. Seira (2021). The Impact of a Private Supplement to Public Health Care: The Mexico Diabetes Experiment. Working Paper 28913, National Bureau of Economic Research.

Carrieri, V. and A. Wuebker (2016). Quasi-Experimental Evidence on the Effects of Health Information on Preventive Behaviour in Europe. *Oxford Bulletin of Economics and Statistics 78*(6), 765–791.

Carrillo, B. and J. Feres (2019). Provider supply, utilization, and infant health: evidence from a physician distribution policy. *American Economic Journal: Economic Policy 11*(3), 156–96.

Chaudhury, N., J. Hammer, M. Kremer, K. Muralidharan, and F. H. Rogers (2006). Missing in action: teacher and health worker absence in developing countries. *Journal of Economic perspectives 20*(1), 91–116.

Chay, K., D. Kim, and S. Swaminathan (2012). Health insurance, hospital utilization and mortality: Evidence from Medicare's origins. Working Paper.

Christensen, D., O. Dube, J. Haushofer, B. Siddiqi, and M. Voors (2020). Building Resilient Health Systems: Experimental Evidence from Sierra Leone and the 2014 Ebola Outbreak. *University of Chicago, Becker Friedman Institute for Economics Working Paper* (2020-28).

Cohen, J. and I. Saran (2018). The impact of packaging and messaging on adherence to malaria treatment: evidence from a randomized controlled trial in Uganda. *Journal of Development Economics 134*, 68–95.

Currie, J., A. Li, and M. Schnell (2023). The effects of competition on physician prescribing. Working Paper 30889, National Bureau of Economic Research.

Currie, J., W. Lin, and J. Meng (2014). Addressing antibiotic abuse in China: An experimental audit study. *Journal of Development Economics 110*, 39–51.

Das, J., A. Chowdhury, R. Hussam, and A. V. Banerjee (2016). The impact of training informal health care providers in India: A randomized controlled trial. *Science 354*(6308), aaf7384.

Das, J., J. Hammer, and K. Leonard (2008). The quality of medical advice in low-income countries. *Journal of Economic Perspectives 22*(2), 93–114.

Das, J., A. Holla, A. Mohpal, and K. Muralidharan (2016). Quality and Accountability in Health Care delivery: audit-study evidence from primary care in India. *American Economic Review 106*(12), 3765–99.

Dinerstein, M., C. Neilson, and S. Otero (2023). The equilibrium effects of public provision in education markets: Evidence from a public school expansion policy. Working Paper.

Dinerstein, M. and T. D. Smith (2021). Quantifying the supply response of private schools to public policies. *American Economic Review 111*(10), 3376–3417.

Dupas, P. (2011). Health behavior in developing countries. *Annual Review of Economics. 3*(1), 425–449.

Ganimian, A., K. Muralidharan, and C. Walters (2021). Augmenting State Capacity for Child Development in India. *NBER Working Paper w28780, National Bureau of Economic Research*.

Garg, S., N. Tripathi, A. Ranjan, and K. K. Bebarta (2022). How much do government and households spend on an episode of hospitalisation in India? A comparison for public and private hospitals in Chhattisgarh state. *Health Economics Review 12*(1), 1–15.

Gertler, P. and C. Vermeersch (2013). Using performance incentives to improve medical care productivity and health outcomes. Working Paper 19046, National Bureau of Economic Research.

Grépin, K. A. (2012). HIV donor funding has both boosted and curbed the delivery of different non-HIV health services in Sub-Saharan Africa. *Health affairs 31*(7), 1406–1414.

Gruber, J., M. Lin, and J. Yi (2023, July). The Largest Insurance Expansion in History: Saving One Million Lives Per Year in China. Working Paper 31423, National Bureau of Economic Research.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political analysis 20*(1), 25–46.

Haushofer, J., M. Kremer, R. Maertens, and B. J. Tan (2021). Water Treatment and Child Mortality: Evidence from Kenya. Working Paper 29447, National Bureau of Economic Research.

Hendren, N. and B. Sprung-Keyser (2020). A unified welfare analysis of government policies. *The Quarterly Journal of Economics 135*(3), 1209–1318.

Hickey, M. D., J. Ayieko, A. Owaraganise, N. Sim, L. B. Balzer, J. Kabami, M. Atukunda, F. J. Opel, E. Wafula, M. Nyabuti, et al. (2021). Effect of a patient-centered hypertension delivery strategy on all-cause mortality: Secondary analysis of SEARCH, a community-randomized trial in rural Kenya and Uganda. *PLoS medicine 18*(9), e1003803.

Islam, S. M. S., T. D. Purnat, N. T. A. Phuong, U. Mwingira, K. Schacht, and G. Fröschl (2014). Non-communicable diseases in developing countries: a symposium report. *Globalization and Health 10*(1), 1–8.

Jiménez-Hernández, D. and E. Seira (2021). Should the government sell you goods? Evidence from the milk market in Mexico. Technical report, Stanford University Working Paper.

Kim, H. K. and J. Niederdeppe (2013). Exploring optimistic bias and the integrative model of behavioral prediction in the context of a campus influenza outbreak. *Journal of health communication 18*(2), 206–222.

Li, Y., J. Meng, C. Song, and K. Zheng (2021). Information avoidance and medical screening: A field experiment in China. *Management Science 67*(7), 4252–4272.

Lin, T., C. Chen, and P. Chou (2004). Impact of the high-risk and mass strategies on hypertension control and stroke mortality in primary health care. *Journal of human hypertension 18*(2), 97–105.

Lopez, C., A. Sautmann, and S. Schaner (2022). Does patient demand contribute to the overuse of prescription drugs? *American Economic Journal: Applied Economics 14*(1), 225–260.

McPake, B. and K. Hanson (2016). Managing the public–private mix to achieve universal health coverage. *The Lancet 388*(10044), 622–630.

MHFW (2023). Ayushman Bharat - Health and Wellness Centre. Ministry of Health & Family Welfare, Government of India. https://ab-hwc.nhp.gov.in/ (accessed on November 14, 2023).

Miguel, E. and M. Kremer (2004). Worms: identifying impacts on education and health in the presence of treatment externalities. *Econometrica 72*(1), 159–217.

Mohanan, M., M. Vera-Hernández, V. Das, S. Giardili, J. D. Goldhaber-Fiebert, T. L. Rabin, S. S. Raj, J. I. Schwartz, and A. Seth (2015). The know-do gap in quality of health care for childhood diarrhea and pneumonia in rural India. *JAMA pediatrics 169*(4), 349–357.

Monami, M., R. Candido, B. Pintaudi, G. Targher, E. Mannucci, L. Delle Monache, M. Gallo, A. Giaccari, M. L. Masini, F. Mazzone, et al. (2021). Effect of metformin on all-cause mortality and major adverse cardiovascular events: An updated meta-analysis of randomized controlled trials. *Nutrition, Metabolism and Cardiovascular Diseases 31*(3), 699–704.

Mora-Garcia, C. A., M. Pesec, and A. M. Prado (2022). The Effect of Primary Health Care on Mortality: Evidence from Costa Rica. *Available at SSRN 4147186*.

Muraleedharan, V. R., U. Dash, S. Vaishnavi, and R. Gopinath (2018). Universal health coverage-pilot in tamil nadu: Has it delivered what was expected? Technical report, Centre for Technology and Policy, Department of Humanities and Social Sciences, IIT Madras, Chennai, Tamil Nadu.

NHSRC (2022). AB-HWC Assessment Report. Technical report.

Okeke, E. N. (2023). When a doctor falls from the sky: The impact of easing doctor supply constraints on mortality. *American Economic Review 113*(3), 585–627.

Okeke, E. N., C. A. Adepiti, and K. O. Ajenifuja (2013). What is the price of prevention? new evidence from a field experiment. *Journal of Health Economics 32*(1), 207–218.

Okwundu, C. I., S. Nagpal, A. Musekiwa, and D. Sinclair (2013). Home-or community-based programmes for treating malaria. *Cochrane Database of Systematic Reviews* (5).

Olaniran, A., B. Madaj, S. Bar-Zev, and N. van den Broek (2019). The roles of community health workers who provide maternal and newborn health services: case studies from Africa and Asia. *BMJ Global Health 4*(4), e001388.

Oster, E., I. Shoulson, and E. R. Dorsey (2013). Optimal expectations and limited medical testing: Evidence from Huntington disease. *American Economic Review 103*(2), 804–830.

Patenaude, B. N., I. Semali, J. Killewo, and T. Bärnighausen (2019). The value of a statistical life-year in Sub-Saharan Africa: evidence from a large population-based survey in Tanzania. *Value in Health Regional Issues 19*, 151–156.

Pyone, T., S. Karvande, S. Gopalakrishnan, V. Purohit, S. Nelson, S. S. Balakrishnan, N. Mistry, and M. Mathai (2019). Factors governing the performance of Auxiliary Nurse Midwives in India: A study in Pune district. *PloS one 14*(12), e0226831.

Rashmi, R. and S. K. Mohanty (2023). Examining chronic disease onset across varying age groups of indian adults using competing risk analysis. *Scientific Reports 13*(1), 5848.

Sankaranarayanan, R., K. Ramadas, G. Thomas, R. Muwonge, S. Thara, B. Mathew, and B. Rajan (2005). Effect of screening on oral cancer mortality in Kerala, India: a cluster-randomised controlled trial. *The Lancet 365*(9475), 1927–1933.

Sant'Anna, P. H. and J. Zhao (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics 219*(1), 101–122.

Shastri, S. S., I. Mittra, G. A. Mishra, S. Gupta, R. Dikshit, S. Singh, and R. A. Badwe (2014). Effect of VIA screening by primary health workers: randomized controlled study in Mumbai, India. *Journal of the National Cancer Institute 106*(3), dju009.

Singh, R. S. (2014). Elderly abuse and neglect: The challenges ahead. *Indian Journal of Health & Wellbeing 5*(3).

Singh, S., N. Dwivedi, A. Dongre, P. Deshmukh, D. Dey, V. Kumar, and S. Upadhyaya (2018). Functioning and time utilisation by female multi-purpose health workers in South India: a time and motion study. *Human Resources for Health 16*(1), 1–11.

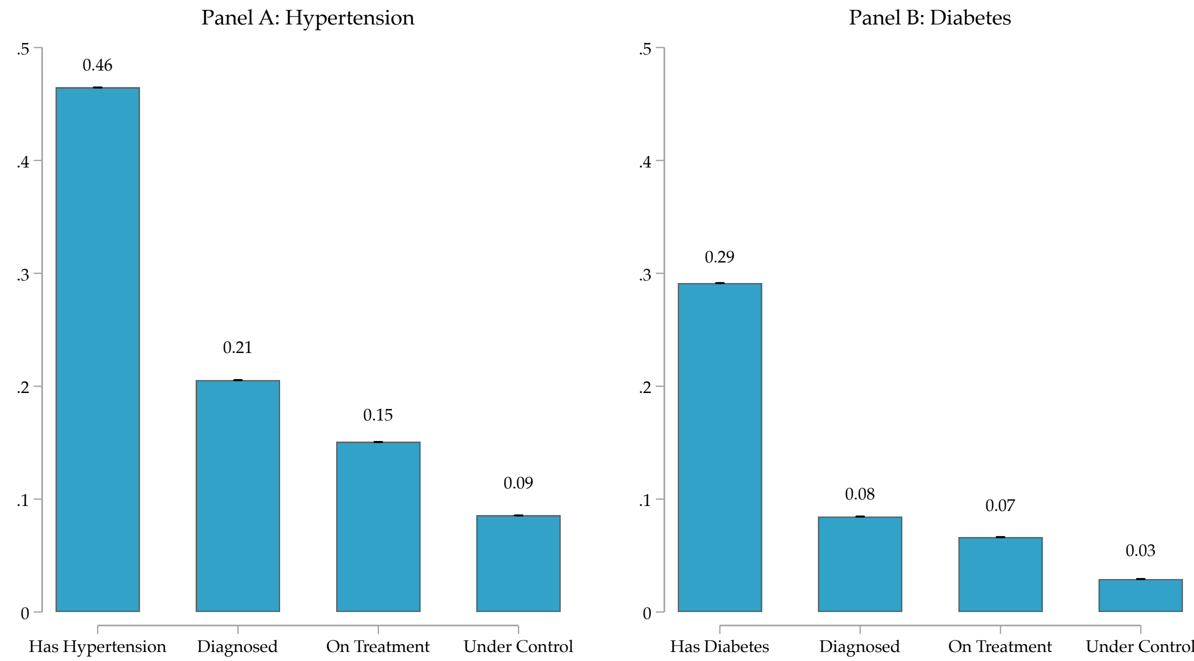
Smith, S., A. Deveridge, J. Berman, J. Negin, N. Mwambene, E. Chingaipe, L. M. Puchalski Ritchie, and A. Martiniuk (2014). Task-shifting and prioritization: a situational analysis examining the role and experiences of community health workers in Malawi. *Human resources for health 12*, 1–13.

Sood, N., E. Bendavid, A. Mukherji, Z. Wagner, S. Nagpal, and P. Mullen (2014). Government health insurance for people below poverty line in India: quasi-experimental evaluation of insurance and health outcomes. *BMJ 349*.

Stuckler, D. (2008). Population causes and consequences of leading chronic diseases: a comparative analysis of prevailing explanations. *The Milbank Quarterly 86*(2), 273–326.

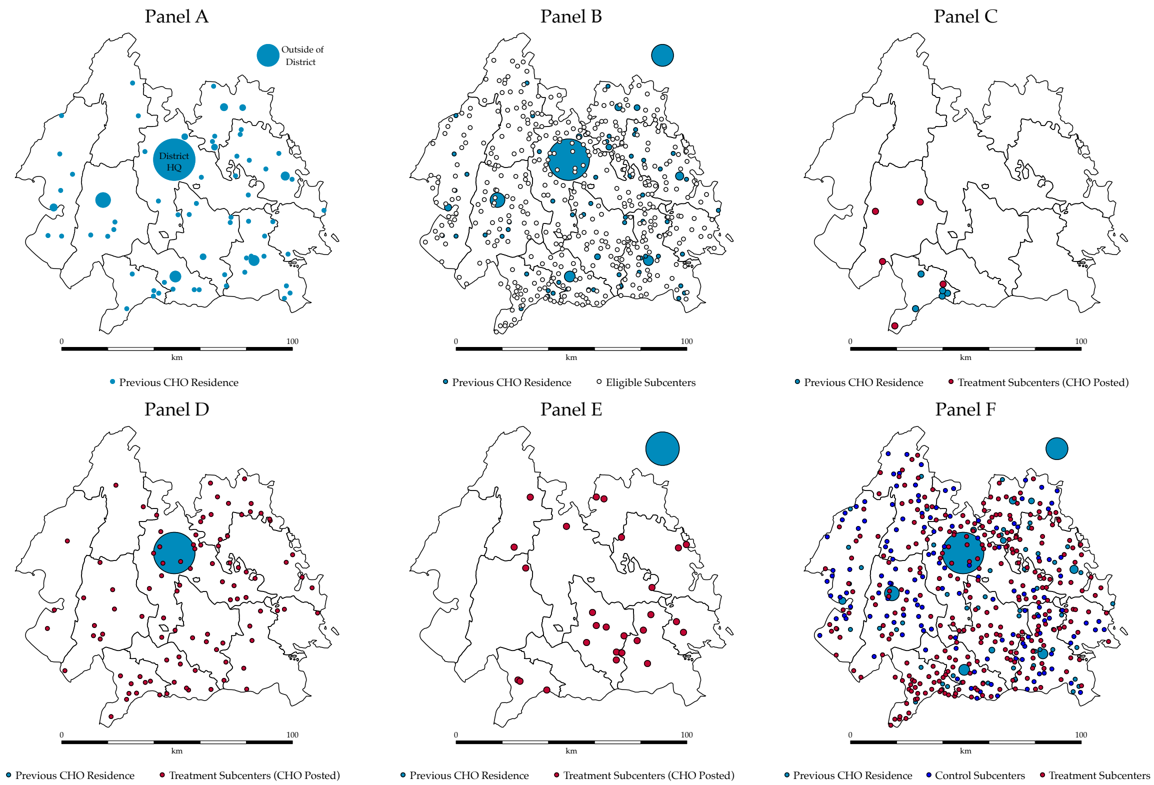
WHO (2023). Hypertension in India. World Health Organization. https://www.who.int/india/health-topics/hypertension (accessed on November 14, 2023).

Figure 1: Hypertension and Diabetes Among the Elderly in Rural India



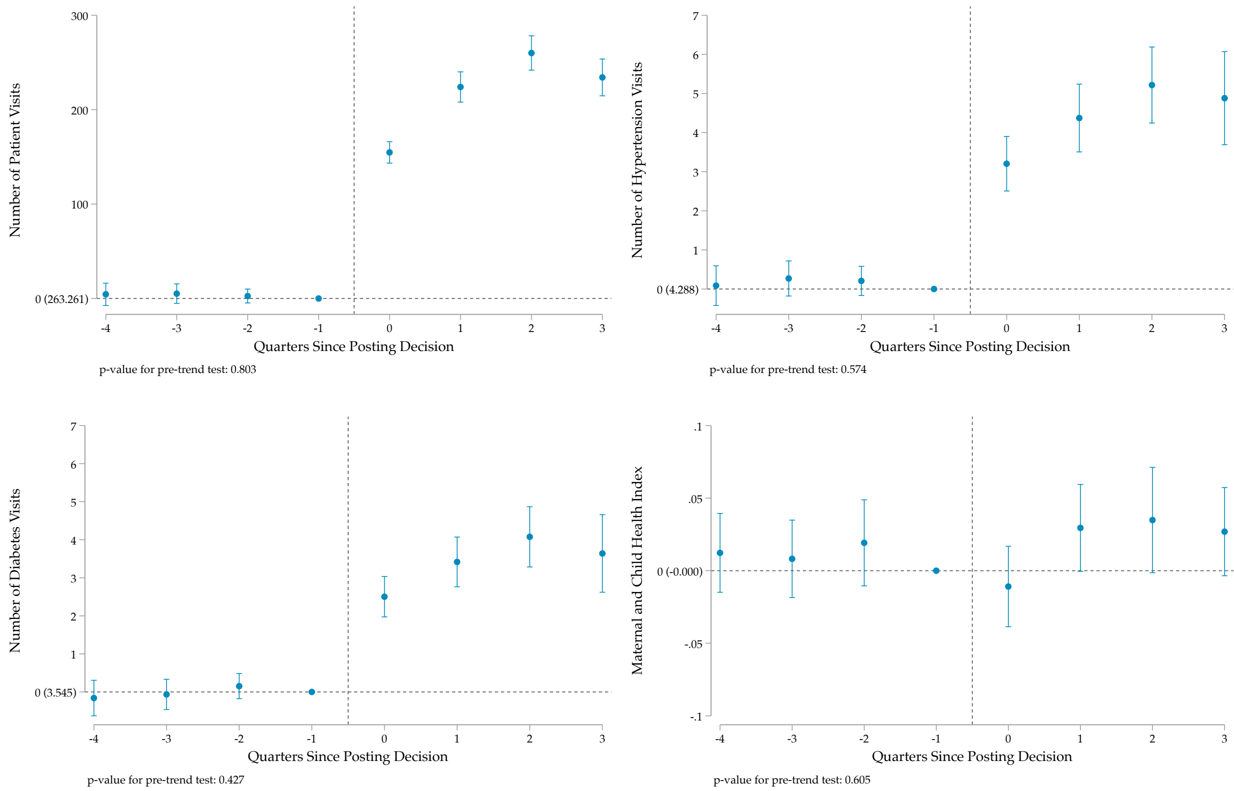
Notes: The figures shows prevalence, diagnosis, and treatment rates for hypertension and diabetes among the elderly in rural India. We classify a person as having hypertension if a person meets at least one of four conditions: (i) a systolic blood pressure of 140 mm Hg or above, (ii) a diastolic rural pressure of 90 or above, (iii) the person was told on on two or more occasions by a doctor that he or she suffers from high blood pressure, (iv) the person reports currently taking medicine to lower blood pressure. For diabetes, a person needs to meet at least one of three conditions: (i) random blood glucose of 140 mg/dL or above, (ii) the person was told on on two or more occasions by a doctor that he or she suffers from high blood sugar, (iii) the person reports currently taking medicine to lower blood sugar. The sample consists of 313,929 household members aged 56 years or older who reside in rural areas. Data are obtained from the National Family Health Survey 5, 2019-21.

Figure 2: Assignments of CHOs Across Udaipur District



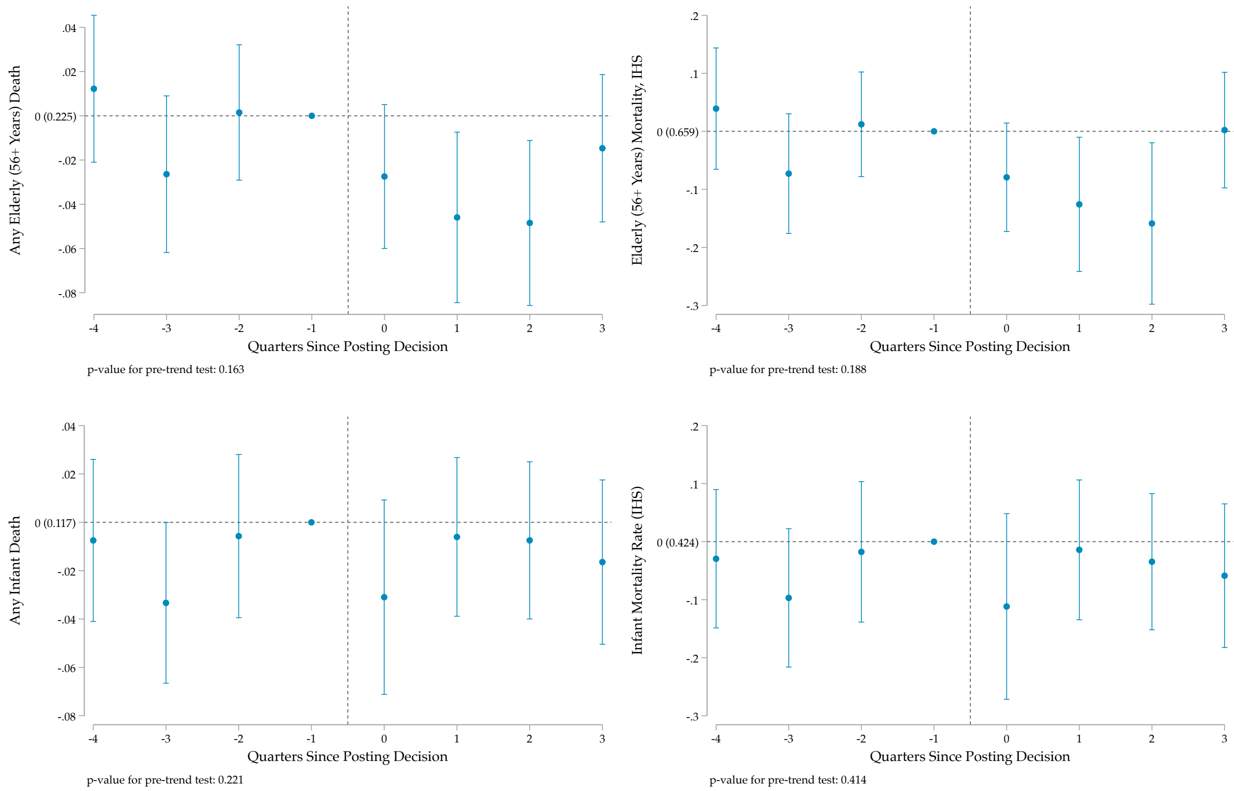
Notes: The figures show where CHOs in Udaipur district previously resided as well as the location of treatment and control subcenters in the district. The boundaries represent subdistricts. The top-left figure shows where CHOs resided before their postings. The size of each bubble represents the number of CHOs in each location. The top-middle figure shows the number of subcenters that were eligible to receive a CHO. The top-right figure indicates the assignment locations for the CHOs that previously resided in Kherwara subdistrict. The bottom-left figure indicates the assignment locations for the CHOs that previously resided in Udaipur city, the district headquarter. The bottom-middle figure indicates the assignment locations for the CHOs that previously resided outside of Udaipur district. The bottom-right figure shows the location of all treatment and control subcenters in the district. Information on previous residence locations are obtained from surveys with 243 CHOs.

Figure 3: Effects of Community Health Officers on Healthcare Services



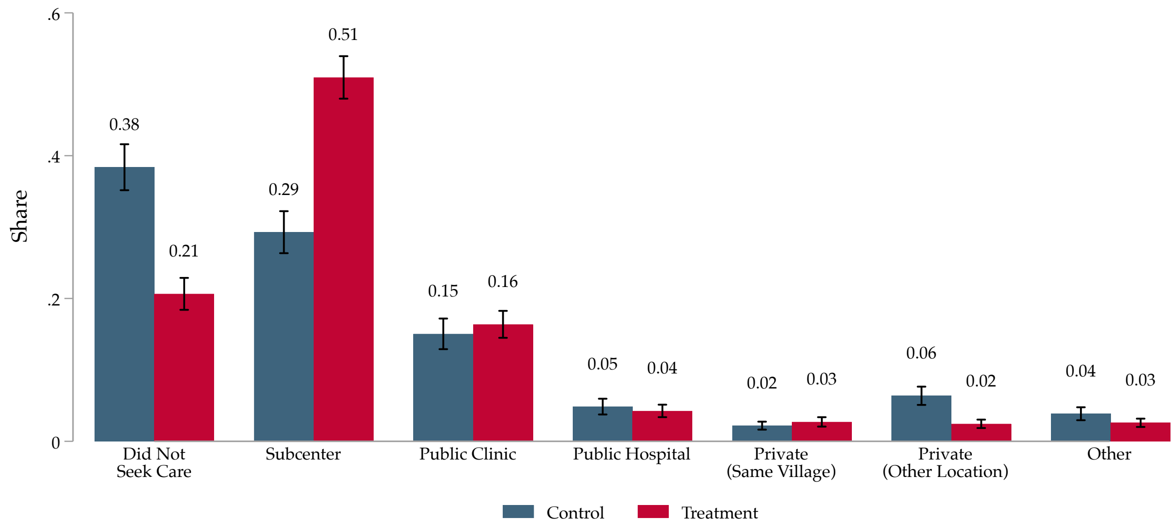
Notes: The figure shows weighted regression estimates of the effect of CHOs on healthcare services. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and quarter dummies, while controlling for year and subcenter fixed effects. The base quarter (Q1 2022) is omitted. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The figures show 95 percent confidence intervals based on standard errors clustered at the subcenter level. The number in parentheses on the y-axis shows the treatment group mean of the outcome in the base quarter. The p-value at the bottom of each figure corresponds to a chi-squared test of the null hypothesis that all interactions between treatment and preperiod dummies are statistically equal to zero. The sample consists of 5,095 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Figure 4: Effects of Community Health Officers on Health Outcomes



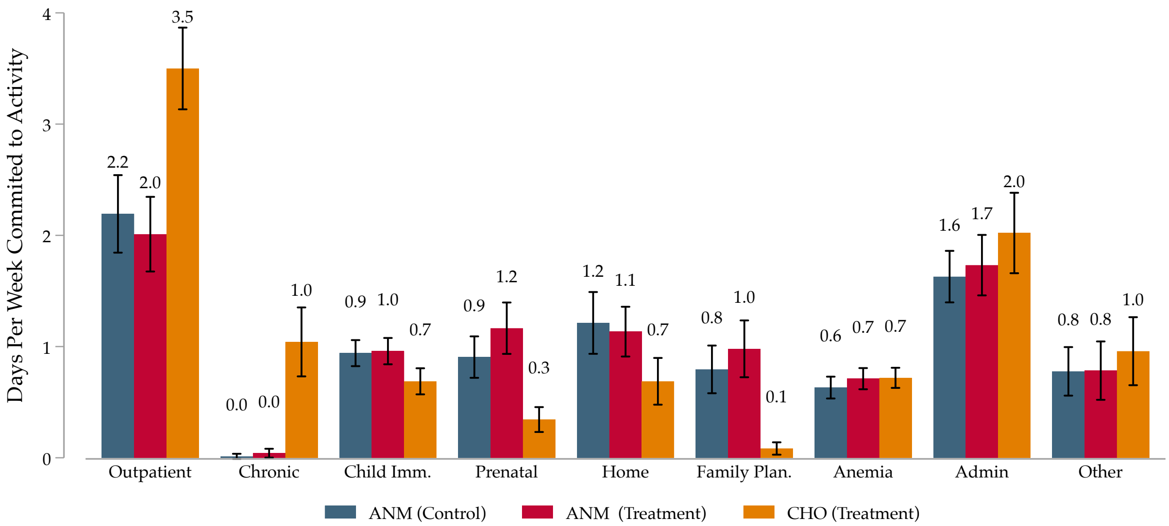
Notes: The figure shows weighted regression estimates of the effect of CHOs on health outcomes. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and quarter dummies, while controlling for year and subcenter fixed effects. The base quarter (Q1 2022) is omitted. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The figures show 95 percent confidence intervals based on standard errors clustered at the subcenter level. The number in parentheses on the y-axis shows the treatment group mean of the outcome in the base quarter. The p-value at the bottom of each figure corresponds to a chi-squared test of the null hypothesis that all interactions between treatment and preperiod dummies are statistically equal to zero. The sample consists of 5,095 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Figure 5: Healthcare Utilization and Provider Choices by Treatment



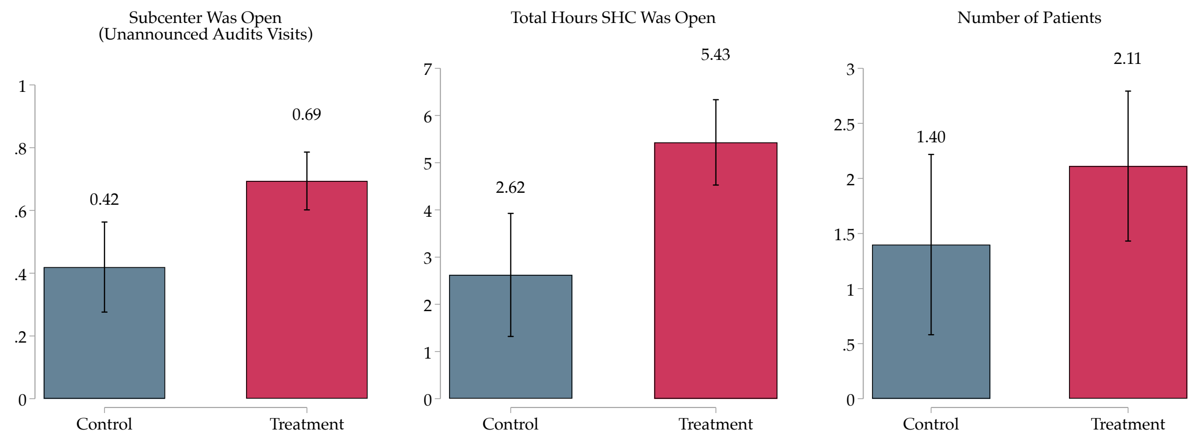
Notes: The figure shows healthcare provider choices in treatment and control group areas. The whiskers correspond to 95% confidence intervals. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample consists of 11,713 respondents (across 881 subcenters) who reported having at least one symptom in the past 30 days. Outcomes are obtained from the second healthcare census of the Community Health Integrated Platform, for which data collection is still ongoing. The figure consists of households surveyed between August and October 2023.

Figure 6: Time Use of ANMs and CHOs



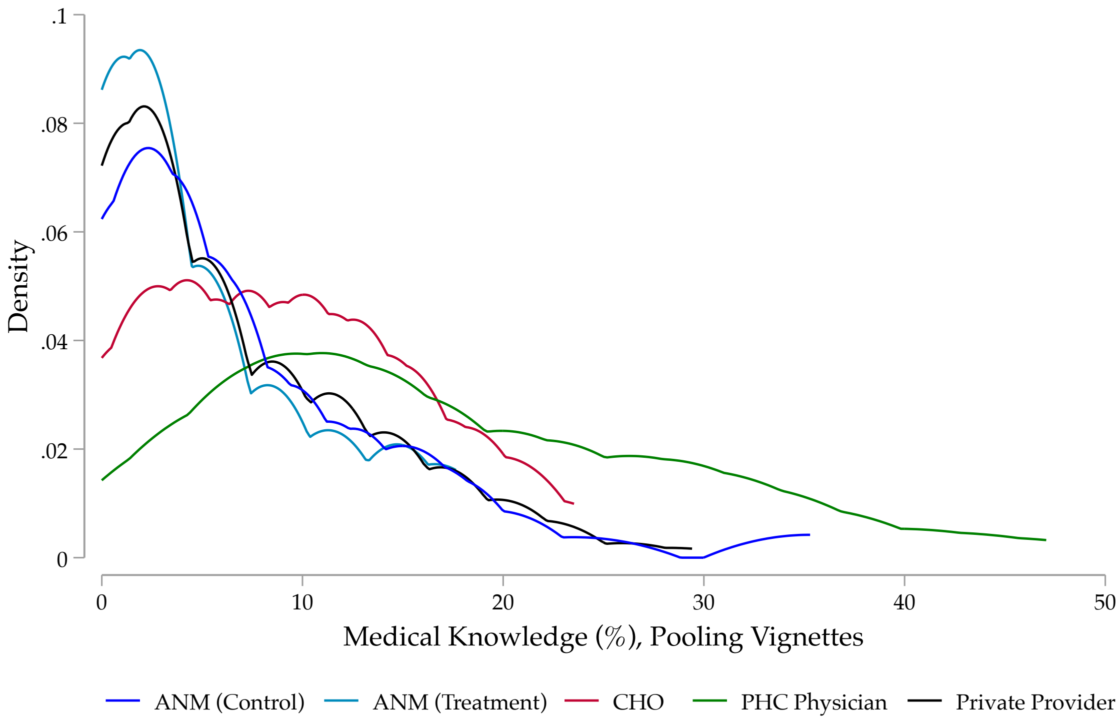
Notes: The figure shows the weighted average number of days per week treatment and control group ANMs and CHOs spent on different activities according to the time-use module in the endline survey. The whiskers correspond to 95% confidence intervals. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. Respondents could select more than one activity per day, so the aggregate number of days can sum up to more than 7 days. The sample consists of 97 control group ANMs, 96 treatment group ANMs, and 96 CHOs.

Figure 7: Results from Unannounced Audit Visits



Notes: The figure shows the results from unannounced visits conducted between March and June 2023. The left figure shows the share of subcenters that were open at least at some point during the day of the unannounced visit. The middle shows the average number of hours for which the subcenters were open. The right figure shows the number of patients observed to have visited the subcenter. The whiskers correspond to 95% confidence intervals. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample consists of 94 control subcenters and 98 treatment subcenters.

Figure 8: Checklist Completion Rates Across Providers



The figure shows the distribution of medical knowledge for different healthcare providers during the endline survey. Medical knowledge is measured as the average checklist completion rates across the child dysentery and adult asthma vignette. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample consists of 97 control group ANMs, 96 treatment group ANMs, 96 CHOs, 49 public clinic physicians, and 207 private providers.

Table 1: Comparison of Treatment and Control Areas

	Original Sample				Reweighted Sample				
	Control Mean (1)	Control St. D. (2)	Treatment Coeff. (3)	Treatment St. E. (4)	Control Mean (5)	Control St. D. (6)	Treatment Coeff. (7)	Treatment St. E. (8)	N (9)
Panel A: Targeted Characteristics									
Distance to District HQ	71.62	[37.61]	-3.17***	(1.04)	68.36	[36.77]	0.09	(1.51)	5,095
Distance to Subdistrict HQ	25.51	[17.51]	-2.59***	(0.44)	23.00	[13.92]	-0.07	(0.53)	5,095
Panel B: Catchment Area Characteristics									
Distance to Public Health Clinic	8.22	[6.62]	-1.23***	(0.17)	7.25	[5.81]	-0.26	(0.22)	5,095
Total Population	2986.10	[1516.00]	153.47***	(43.78)	3057.10	[1596.83]	82.47	(70.74)	5,095
Elderly Population Share	0.09	[0.04]	0.00	(0.00)	0.09	[0.04]	0.00	(0.00)	5,040
Scheduled Caste Share	0.19	[0.15]	-0.02***	(0.00)	0.16	[0.12]	0.01**	(0.00)	5,095
Scheduled Tribe Share	0.17	[0.28]	0.03***	(0.01)	0.20	[0.31]	-0.00	(0.01)	5,095
Female Share	0.49	[0.02]	0.00*	(0.00)	0.49	[0.02]	-0.00	(0.00)	5,095
Literacy Rate	0.47	[0.10]	0.03***	(0.00)	0.50	[0.11]	0.01*	(0.00)	5,095
Land Ownership Rate	0.69	[0.19]	0.04***	(0.01)	0.72	[0.18]	0.00	(0.01)	5,041
Employment Rate	0.50	[0.08]	-0.01***	(0.00)	0.49	[0.09]	0.00	(0.00)	5,095
(Imputed) Consumption per Capita	16551.53	[3693.90]	658.70***	(107.67)	16971.03	[3963.52]	239.21	(160.31)	5,041
Panel C: Average Facility Indicators in Q1 2022									
Number of Patients	263.26	[218.29]	-24.17***	(5.56)	242.59	[205.01]	-3.51	(8.44)	5,095
Number of Hypertension Patients	4.29	[9.53]	-0.33	(0.24)	4.23	[8.63]	-0.26	(0.31)	5,095
Number of Diabetes Patients	3.54	[7.68]	-0.05	(0.20)	3.53	[6.90]	-0.03	(0.26)	5,095
Maternal and Child Health Services Index	-0.00	[0.75]	0.02	(0.02)	0.00	[0.75]	0.02	(0.03)	5,095
Elderly Mortality Rate	2.85	[7.39]	-0.05	(0.20)	2.88	[7.55]	-0.09	(0.30)	5,095
Infant Mortality Rate	2.59	[8.33]	-0.23	(0.22)	2.28	[7.53]	0.09	(0.28)	5,095

Notes: This table shows the means of selected covariates for the original and reweighted sample. Panel A reports on the covariates used to estimate the propensity score for the inverse probability weighting. Panel B reports on covariates at the catchment area level. Catchment-level covariates are calculated based on population-weighted averages across all villages in the catchment area of the respective subcenter. Panel C reports on the main outcomes in the pre-treatment reference period. Columns (1)-(4) present the original sample and columns (5)-(8) present the reweighted sample. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. Differences in sample sizes across variables reflect missing data. Columns (1) and (5) report the control mean of the dependent variable for each relevant sample. Columns (3), and (7) report the difference in the dependent variable from OLS regressions of each outcome on an indicator variable for CHO assignment.

Table 2: Effects of Community Health Officers on Healthcare Services

	Number of Patient Visits (1)	Number of Hypertension Patient Visits (2)	Number of Diabetes Patient Visits (3)	Maternal & Child Health Services Index (4)
Treatment × Post	215.191***	4.277***	3.427***	0.010
	(6.582)	(0.390)	(0.311)	(0.010)
Control Group Mean (Pre-Periods)	244.221	4.035	3.383	0.019
Treatment Group Mean (Pre-Periods)	243.761	3.913	3.330	0.047
Counterfactual Treatment Group Mean (Post-Periods)	316.622	6.413	5.485	0.149
Observations	10,190	10,190	10,190	10,190

Notes: This table shows the effects of CHOs on healthcare services. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample consists of 5,095 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System. Appendix Table A5 provides regression estimates for each index component in the maternal and child health index in column (4).

Table 3: Effects of Community Health Officers on Health Outcomes

	Elderly (56+) Mortality				Infant Mortality			
	Any Death	Number of Deaths	Mortality Rate	Mortality Rate (IHS)	Any Death	Number of Deaths	Mortality Rate	Mortality Rate (IHS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post	-0.031***	-0.083**	-0.328*	-0.090**	-0.004	-0.002	-0.191	-0.019
	(0.011)	(0.037)	(0.197)	(0.035)	(0.009)	(0.013)	(0.249)	(0.034)
Control Group Mean (Pre-Periods)	0.237	0.688	3.028	0.707	0.134	0.178	2.701	0.475
Treatment Group Mean (Pre-Periods)	0.256	0.723	3.007	0.743	0.133	0.178	2.669	0.472
Counterfactual Treatment Group Mean (Post-Periods)	0.275	0.696	2.907	0.776	0.148	0.194	3.025	0.527
Observations	10,190	10,190	10,190	10,190	10,190	10,190	10,190	10,190

Notes: This table shows the effects of CHOs on healthcare services. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample consists of 5,095 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table 4: Effects of Community Health Officers on Health Outcomes in Household Surveys

	All Household Members			
	Past 30 Days		Past 6 Months	
	Any Symptoms (1)	Medical Expenses (2)	Any Hospi-talization (3)	Hospital Days (4)
Treatment × Post	0.013	-7.152	-0.017**	-0.049**
	(0.032)	(48.999)	(0.008)	(0.021)
Control Group Mean (Pre-Period)	0.098	119.684	0.024	0.060
Treatment Group Mean (Pre-Period)	0.092	149.069	0.036	0.090
Counterfactual Treatment Group Mean (Post-Period)	0.162	237.953	0.033	0.086
Observations	5,849	5,792	5,850	5,849

Notes: This table shows the effects of CHOs on healthcare services at the household member level. The regression coefficients are estimated by regressing the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details.

Table 5: Results from Patient Exit Surveys at Endline

	Overall Satisfaction	Number of Questions Asked	Measured Blood Pressure	Any Antibiotics	Referred
	(1)	(2)	(3)	(4)	(5)
Treatment	0.376**	0.545**	0.231***	0.051	0.085***
	(0.180)	(0.209)	(0.070)	(0.077)	(0.031)
Mean of Outcome	4.108	1.725	0.066	0.105	0.010
Observations	172	173	177	177	174

Notes: This table shows the effects of CHOs on healthcare quality according to patient exit survey. In each column, we regress the outcome on an indicator variable for whether a CHO was assigned to the subcenter in March 2022. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample consists of 177 patients who visited the subcenter for outpatient care services. The satisfaction outcome ranges from 1 (lowest) to 5 (highest).

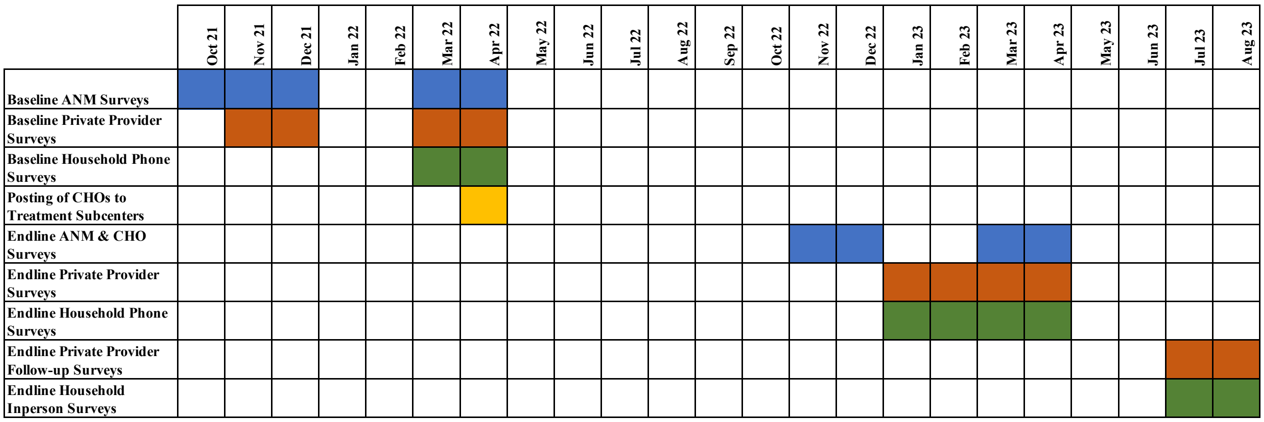
Table 6: Effects of Community Health Officers on Private Provider Behavior

	Number of Patients (1)	Typical Fee (2)	Quality Index (3)
Panel A: Pooled			
Treatment × Post	-6.547	5.380	0.196*
	(23.180)	(14.642)	(0.108)
Control Group Mean (Baseline)	96.776	106.793	-0.017
Treatment Group Mean (Baseline)	104.108	102.800	0.070
Counterfactual Treatment Group Mean (Endline)	125.507	112.548	0.055
Observations	450	453	473
Panel B: Heterogeneity by Distance			
Treatment × Post × Close Providers	12.954	-5.585	0.372***
	(25.901)	(14.759)	(0.135)
Treatment × Post × Distant Providers	-57.051	17.945	-0.092
	(43.352)	(29.129)	(0.161)
p-value: Coef 1 = Coef 2	0.144	0.462	0.027
Close Providers:			
Control Group Mean (Pre-Period)	97.685	94.268	0.014
Treatment Group Mean (Pre-Period)	103.186	98.913	-0.073
Counterfactual Treatment Group Mean (Post-Periods)	111.590	116.179	-0.124
Observations	289	298	310
Distant Providers:			
Control Group Mean (Pre-Period)	95.479	126.849	-0.069
Treatment Group Mean (Pre-Period)	105.387	108.966	0.298
Counterfactual Treatment Group Mean (Post-Periods)	164.953	114.506	0.351
Observations	161	155	163

Notes: This table shows the effects of CHOs on healthcare services. In Panel A, we regress the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them. In Panel B, we regress the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them, separately for distant and close providers. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample pools the baseline survey round and two endline survey rounds. We define close providers as private providers that are not more than 500 meters away from the subcenter building. Appendix Table A20 provides regression estimates for each index component in the quality index in column (3).

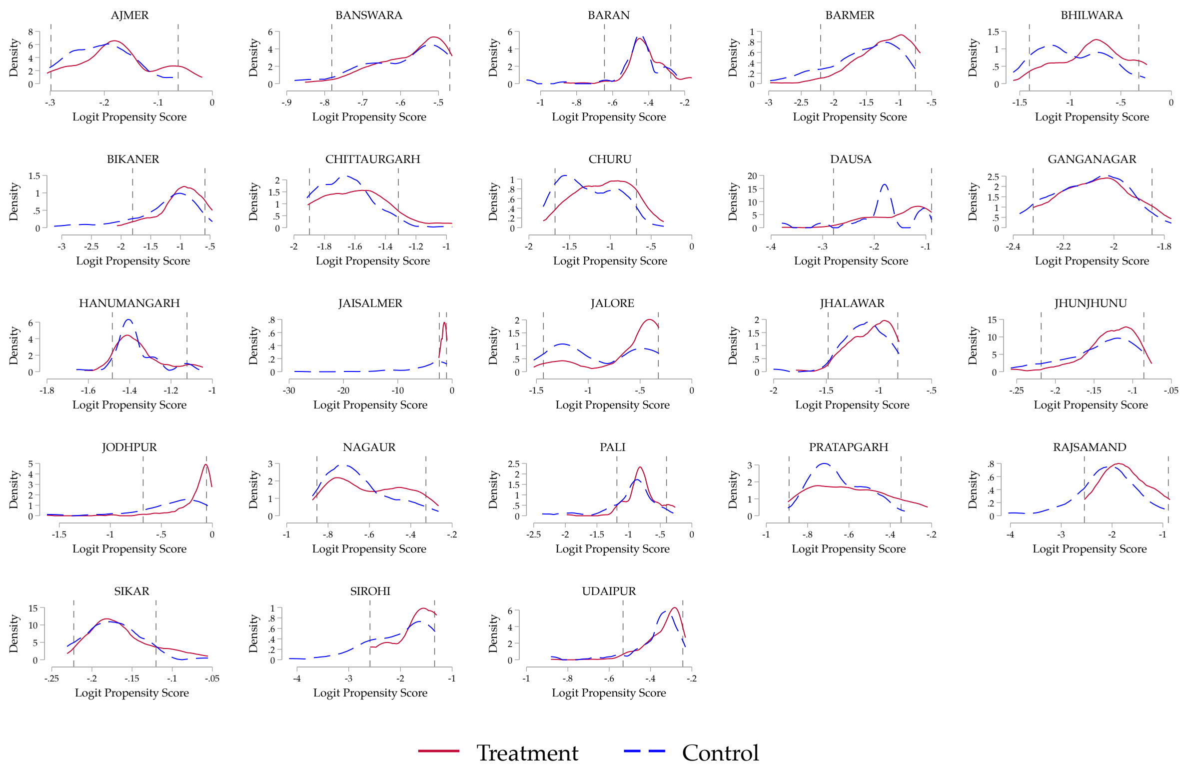
A. Appendix Tables and Figures

Figure A1: Timeline



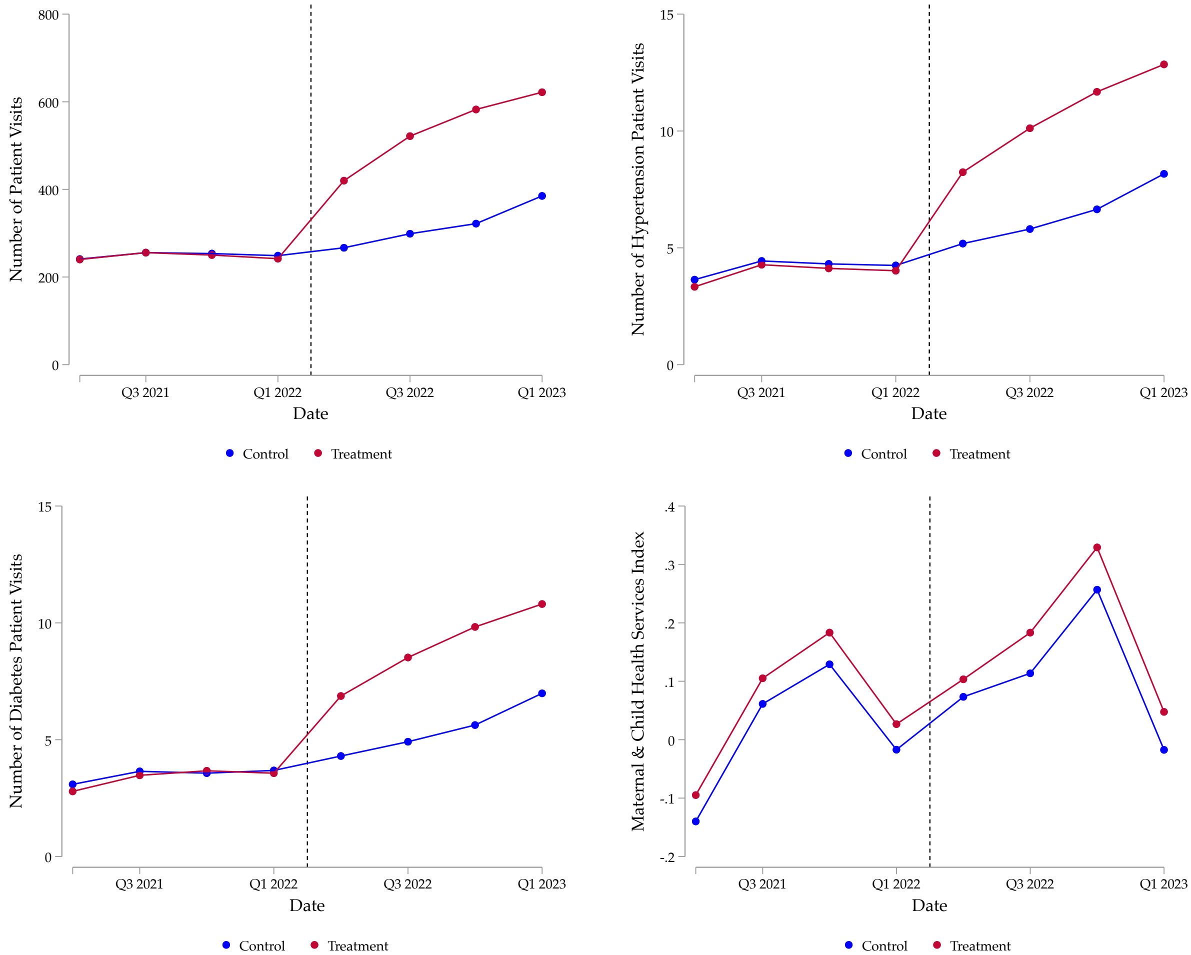
Notes: This figure shows the timeline for the primary data collection. The assignments of CHOs to subcenters were announced on March 27, 2022. Most CHOs started to work in the field by the end of April. Household inperson surveys at endline were done with households that were surveyed over the phone at baseline but could not be reached over the phone at endline. See Appendix Table A2 for survey completion rates.

Figure A2: Common Support Restrictions

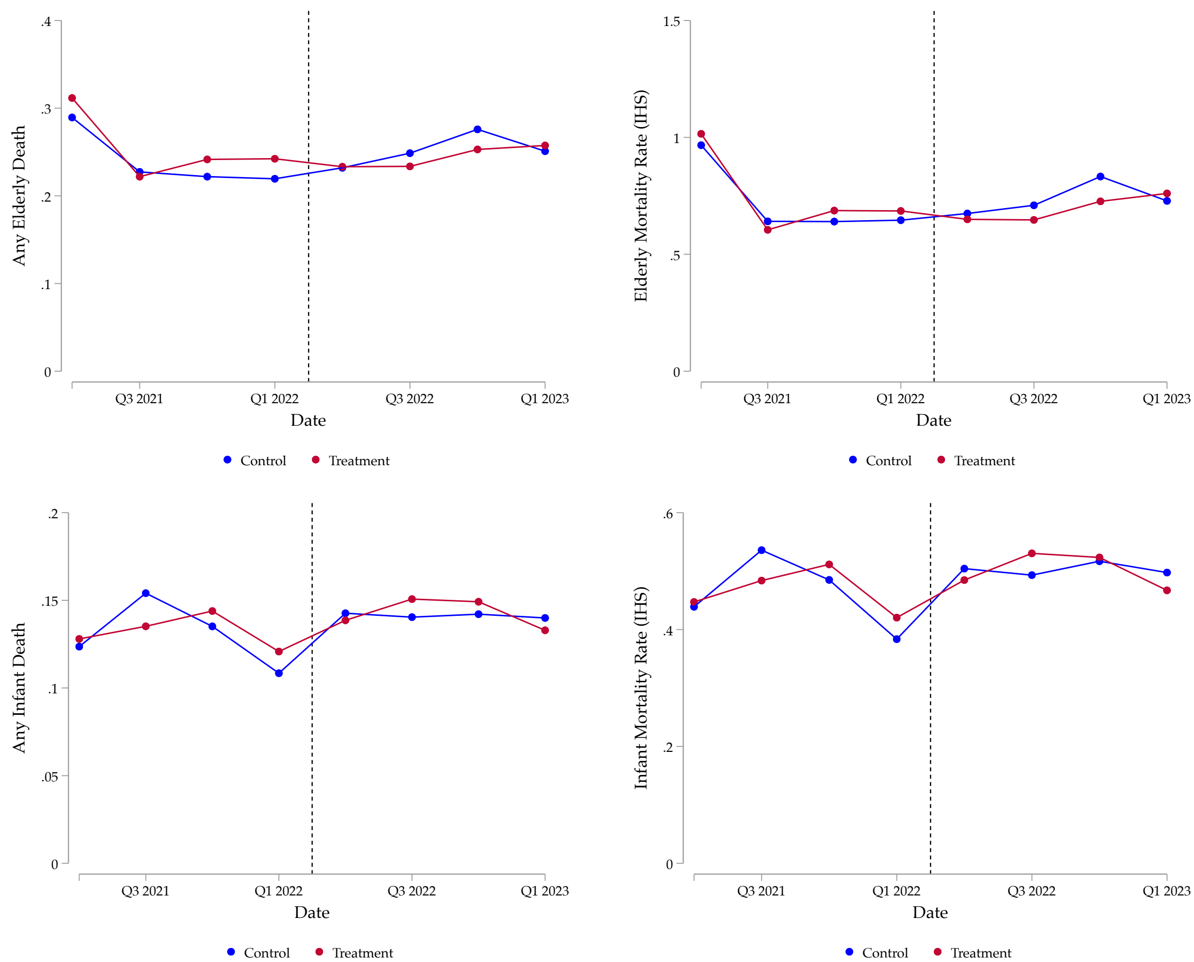


Notes: This figure shows the distribution of the logit propensity score in each district within our sample for treatment and control group facilities. Districts in which more than 90% of converted subcenters received a CHO are omitted. Propensity scores are estimates by a logistic regression that regresses the treatment dummy on linear and squared terms of the subcenter's distance to the district and block headquarters. In our preferred specification, we implement common support restrictions by excluding observations within the top or bottom 2.5 percent of either the control or treatment propensity score distribution in each district (vertical lines). See Appendix Table A8 for robustness regarding alternative common support restrictions.

Figure A3: Trends in Main Outcomes by Treatment Group

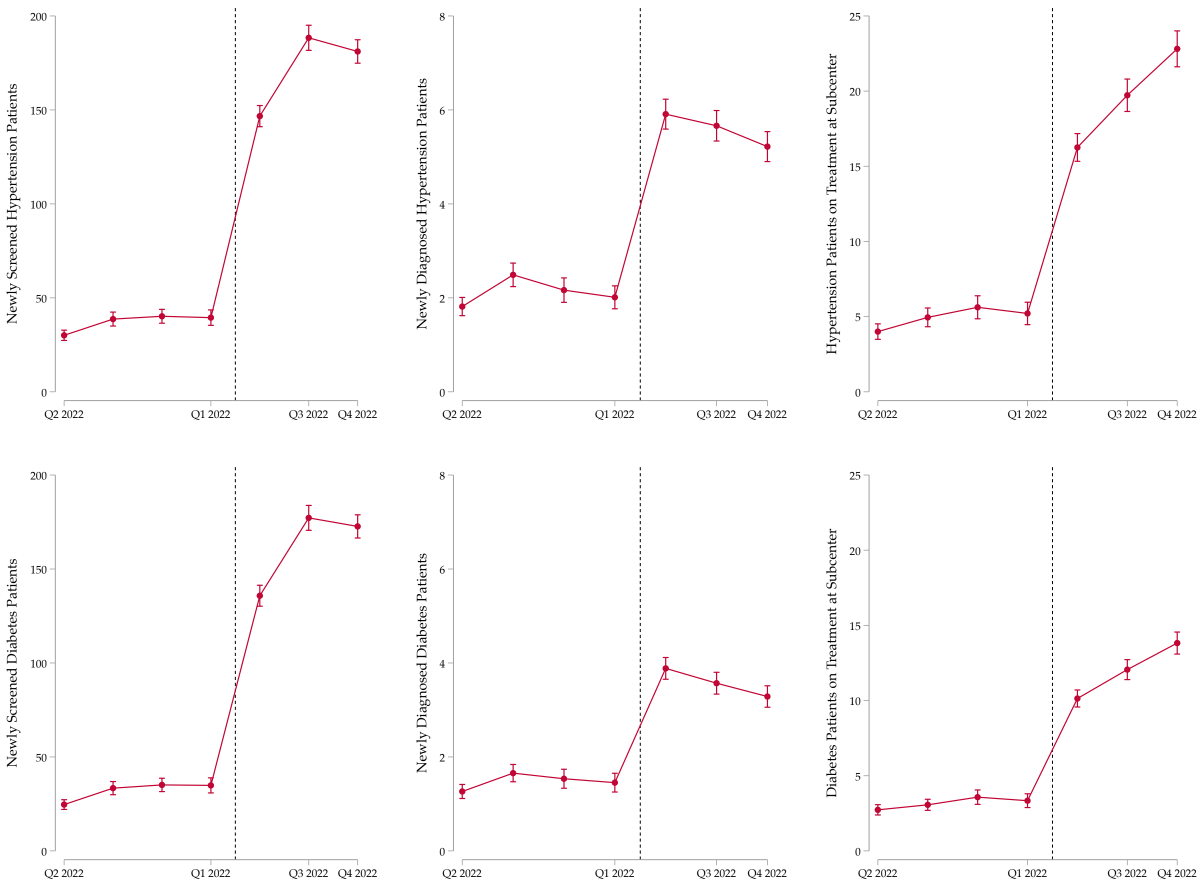


Trends in Main Outcomes by Treatment Group (Continued)



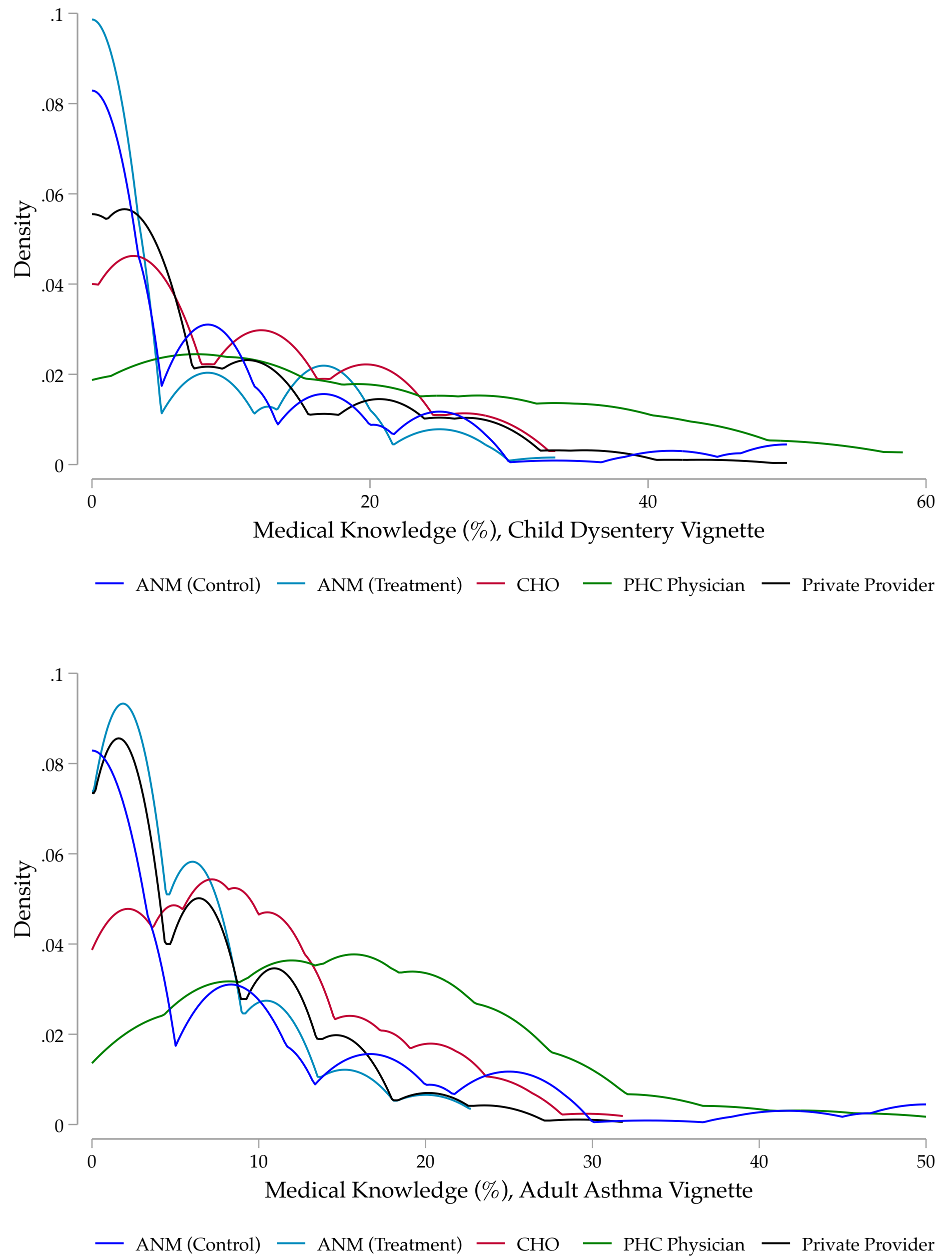
Notes: The figure shows weighted means for our main outcomes for treatment and control subcenters over time. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample consists of 5,095 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Figure A4: Hypertension and Diabetes Patients at Treatment Subcenters Over Time



Notes: The figure shows the provision of chronic diseases services for treatment subcenters over time. Information for control subcenters areas not shown since they stopped reporting after the first batch of CHOs was posted. The sample consists of 2,545 treatment subcenters and the sample period covers Q2 2021 until Q4 2022. Outcomes are obtained from the Health and Wellness Center Portal.

Figure A5: Checklist Completion Rates Across Providers by Vignette



Notes: The figure shows the distribution of medical knowledge for different healthcare providers during the endline survey, separately for the child dysentery and the adult asthma vignette. Medical knowledge is measured as the average checklist completion rates across the child dysentery and adult asthma vignette. The sample consists of 97 control group ANMs, 96 treatment group ANMs, 96 CHOs, 49 public clinic physicians, and 207 private providers.

Table A1: Incentive Payments

S. No.	**Indicators**	**CHO**	**ASHA**	**ANM**
1	Proportion of Pregnant Women registered who received ANC as per scheduled due date	1000	67	100
2	Proportion of new-borns who received Home Based Newborn Care services	1000	67	100
3a	Proportion of Children up to 1 years of age who received immunization as per the due date	500	33	50
3b	Proportion of Children up to 2 years of age who received immunization as per the due date	500	33	50
4	Proportion of cases referred for TB screening	1000	67	100
5	Number of footfalls in the month	1000	67	100
6	Proportion of individuals 30 years and above whose CBAC form was filled	1000	67	100
7a	Proportion of individual 30 years or above screened for Hypertension	500	33	50
7b	Proportion of Hypertension patients on treatment	500	33	50
8a	Proportion of individual 30 years or above screened for Diabetes	500	33	50
8b	Proportion of Diabetes patients on treatment	500	33	50
9	Teleconsultation Services	1000	67	100
10	Wellness sessions Organised at HWCs	1000	67	100
11	Wellness Activities held as per annual Health calendar	1000	67	100
12	Monthly JAS meeting held with minimum 60% of the members	1000	67	100
13	Village Meetings	1000	67	100
14	MCHN held against planned	1000	67	100
15a	Monitoring of Referral cases – Upward	500	33	50
15b	Monitoring Of Referral cases - Downward/ Follow up	500	33	50
		15000	**1000**	**1500**

Notes: The table shows the monthly incentive payments CHOs, ASHAs, and ANMS receive for completing their targets. The payments are denoted in INR.

Table A2: Survey Completion Rates

	Public Providers		Private Providers			Households	
	Baseline Completion Rate	Endline Completion Rate	Baseline Completion Rate	Endline Round 1 Follow-Up Rate	Endline Round 2 Follow-Up Rate	Baseline Completion Rate	Endline Follow-Up Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.019	-0.020	-0.013	0.001	-0.008	-0.012	-0.019
	(0.029)	(0.014)	(0.064)	(0.050)	(0.073)	(0.022)	(0.031)
Control Group Mean	0.968	1.000	0.711	0.882	0.663	0.267	0.910
Observations	193	193	280	169	169	1,971	512

Notes: This table shows differences in survey completion rates by treatment status. In each column, we regress a dummy for whether the survey was completed on a treatment dummy. The sample in columns 1-2 consists of 193 ANMs. The sample in column 3 consists of 280 private healthcare providers that we mapped across the 193 catchment areas. The sample in columns 4 and 5 consists of private providers that were surveyed at baseline and still operational at endline. The second follow-up survey was partly done over the phone. The sample in column 6 consists of households that have registered pregnancy in the past five years. The sample in column 7 consists of all households that were surveyed at baseline. The endline survey was partly done in person.

Table A3: Comparison of Treatment and Control Areas in Survey Sample

	Original Sample				Reweighted Sample				
	Control Mean (1)	Control St. D. (2)	Treatment Coeff. (3)	Treatment St. E. (4)	Control Mean (5)	Control St. D. (6)	Treatment Coeff. (7)	Treatment St. E. (8)	N (9)
Panel A: Targeted Characteristics									
Distance to District HQ	67.09	[21.07]	-8.69***	(2.95)	57.21	[19.44]	1.18	(3.30)	193
Distance to Subdistrict HQ	23.03	[12.61]	-3.27*	(1.77)	18.72	[10.57]	1.05	(1.66)	193
Subcenter Has Electricity	0.69	[0.46]	-0.07	(0.07)	0.60	[0.49]	0.03	(0.09)	193
Subcenter Has Running Water	0.31	[0.46]	0.12*	(0.07)	0.39	[0.49]	0.04	(0.09)	193
Subcenter Building in Good Condition	0.31	[0.46]	0.16**	(0.07)	0.49	[0.50]	-0.03	(0.09)	193
Panel B: Catchment Area Characteristics									
Distance to Public Health Clinic	6.90	[5.31]	-0.36	(0.87)	7.66	[6.93]	-1.12	(1.28)	193
Total Population	3082.30	[1254.20]	266.88	(189.28)	3190.21	[1364.64]	158.97	(257.48)	193
Scheduled Caste Share	0.06	[0.05]	0.01*	(0.01)	0.07	[0.05]	0.00	(0.01)	185
Scheduled Tribe Share	0.46	[0.32]	-0.07	(0.05)	0.36	[0.29]	0.04	(0.05)	185
Female Share	0.49	[0.01]	-0.00	(0.00)	0.49	[0.01]	-0.00	(0.00)	185
Literacy Rate	0.47	[0.08]	0.01	(0.01)	0.49	[0.07]	-0.01	(0.01)	185
Land Ownership Rate	0.68	[0.14]	-0.00	(0.02)	0.70	[0.12]	-0.02	(0.02)	184
Employment Rate	0.50	[0.09]	-0.01	(0.01)	0.50	[0.09]	-0.02	(0.02)	185
(Imputed) Consumption per Capita	15264.34	[3352.43]	766.40	(482.08)	16417.50	[3236.80]	-386.75	(559.93)	184
Panel C: Average Facility Indicators in Q1 2022									
Number of Patients	208.22	[143.74]	23.82	(19.45)	254.89	[193.32]	-22.85	(34.32)	193
Number of Hypertension Patients	3.66	[7.26]	0.07	(1.15)	3.59	[6.81]	0.14	(1.26)	193
Number of Diabetes Patients	2.90	[5.22]	0.31	(0.91)	3.16	[5.17]	0.05	(1.06)	193
Maternal and Child Health Services Index	0.00	[0.68]	0.25**	(0.11)	-0.01	[0.71]	0.26*	(0.14)	193
Elderly Mortality Rate	0.97	[3.14]	0.47	(0.46)	0.96	[2.82]	0.48	(0.50)	193
Infant Mortality Rate	12.94	[39.20]	-1.03	(5.46)	12.72	[40.09]	-0.81	(6.56)	193

Notes: This table shows the means of selected covariates for the original and reweighted survey sample. Panel A reports on the covariates used to estimate the propensity score for the inverse probability weighting. Panel B reports on covariates at the catchment area level. Catchment-level covariates are calculated based on population-weighted averages across all villages in the catchment area of the respective subcenter. Panel C reports on the main outcomes in the pre-treatment reference period. Columns (1)-(4) present the original sample and columns (5)-(8) present the reweighted sample. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. Differences in sample sizes across variables reflect missing data. Columns (1) and (5) report the control mean of the dependent variable for each relevant sample. Columns (3), and (7) report the difference in the dependent variable from OLS regressions of each outcome on an indicator variable for CHO assignment.

Table A4: Effects of Community Health Officers on Elderly Mortality by Causes of Death

	Elderly (56+ Years) Deaths			
	Chronic	Acute	Accident	Unknown Cause
	(1)	(2)	(3)	(4)
Panel A: Any Death				
Treatment × Post	-0.012	-0.003	0.000	-0.035***
	(0.008)	(0.006)	(0.003)	(0.011)
Control Group Mean (Pre-Periods)	0.096	0.050	0.009	0.161
Treatment Group Mean (Pre-Periods)	0.106	0.056	0.013	0.176
Counterfactual Treatment Group Mean (Post-Periods)	0.103	0.056	0.015	0.205
Observations	10,190	10,190	10,190	10,190
Panel B: Mortality Rate (IHS)				
Treatment × Post	-0.026	-0.009	0.000	-0.087***
	(0.021)	(0.014)	(0.005)	(0.033)
Control Group Mean (Pre-Periods)	0.245	0.116	0.016	0.462
Treatment Group Mean (Pre-Periods)	0.262	0.131	0.022	0.483
Counterfactual Treatment Group Mean (Post-Periods)	0.245	0.131	0.026	0.540
Observations	10,190	10,190	10,190	10,190

Notes: This table shows the effects of CHOs on elderly mortality for different causes of death. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample consists of 5,095 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table A5: Effects of Community Health Officers on Maternal and Child Health Services Index Components

	Maternal & Child Health Services Index Components							
	N Pregnant Women							
	Registered	4+ Prenatal Care Visits	Calcium tables	1st Tetanus Shot	N Children Fully Immunized	N Postnatal Care Visits	N Children Given Al-bendazole	N Low Birthweight Babies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post	0.094	0.143	-0.050	0.144	0.154	-0.140	2.570	-0.079
	(0.145)	(0.149)	(0.233)	(0.112)	(0.118)	(0.138)	(2.044)	(0.067)
Control Group Mean (Pre-Periods)	16.447	10.519	11.212	9.980	14.695	8.806	39.602	1.676
Treatment Group Mean (Pre-Periods)	16.599	10.683	11.594	10.206	14.898	9.218	40.960	1.609
Counterfactual Treatment Group Mean (Post-Periods)	15.952	12.601	13.947	10.754	14.927	10.752	43.098	1.403
Observations	10,190	10,190	10,190	10,190	10,190	10,190	10,190	10,190

Notes: This table shows the effects of CHOs on the components of the maternal and child health services index as well as the number of newborns with low birthweight. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample consists of 5,095 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table A6: Effects of Community Health Officers on Mortality Outcomes for Other Age Groups

	Deaths by Age Group		
	Child (1-4 Years) (1)	Adolescent (5-14 Years) (2)	Adult (15-55 Years) (3)
Panel A: Any Death			
Treatment × Post	-0.011	-0.001	0.005
	(0.010)	(0.001)	(0.004)
Control Group Mean (Pre-Periods)	0.101	0.001	0.033
Treatment Group Mean (Pre-Periods)	0.109	0.003	0.029
Counterfactual Treatment Group Mean (Post-Periods)	0.085	0.004	0.026
Observations	10,190	10,190	10,190
Panel B: Mortality Rate (IHS)			
Treatment × Post	0.018	-0.002	-0.006
	(0.014)	(0.001)	(0.009)
Control Group Mean (Pre-Periods)	0.107	0.001	0.095
Treatment Group Mean (Pre-Periods)	0.094	0.003	0.100
Counterfactual Treatment Group Mean (Post-Periods)	0.083	0.004	0.070
Observations	10,190	10,190	10,190

Notes: This table shows the effects of CHOs on mortality outcomes for different age groups. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample consists of 5,095 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table A7: Effects of Community Health Officers on Hospitalizations by Age Group

	Any Hospitalization		
	Child (1)	Adult (2)	Elderly (3)
Treatment × Post	0.007	-0.018	-0.043*
	(0.012)	(0.014)	(0.023)
Control Group Mean (Pre-Period)	0.011	0.047	0.014
Treatment Group Mean (Pre-Period)	0.008	0.065	0.039
Counterfactual Treatment Group Mean (Post-Period)	0.001	0.041	0.074
Observations	2,075	2,215	1,276

Notes: This table shows the effects of CHOs on hospitalizations at the household member level for different age groups. The regression coefficients are estimated by regressing the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. Outcomes are obtained from our household surveys.

Table A8: Robustness Regarding Common Support Restrictions

	Number of Patient Visits	Number of Hypertension Patient Visits	Number of Diabetes Patient Visits	Maternal & Child Health Services Index	Any Elderly Death	Elderly Mortality Rate (IHS)	Any Infant Death	Infant Mortality Rate (IHS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Districts with 10-90% Assignment Rate, Minimal Common Support Restriction								
Treatment × Post	217.990***	4.681***	3.794***	0.013	-0.026**	-0.077**	-0.002	-0.011
	(6.639)	(0.385)	(0.317)	(0.010)	(0.010)	(0.032)	(0.009)	(0.032)
Observations	11,002	11,002	11,002	11,002	11,002	11,002	11,002	11,002
Panel B: Districts with 10-90% Assignment Rate , 1% Common Support Restriction								
Treatment × Post	217.327***	4.597***	3.711***	0.014	-0.027***	-0.079**	0.000	-0.003
	(6.702)	(0.388)	(0.318)	(0.010)	(0.010)	(0.032)	(0.009)	(0.032)
Observations	10,784	10,784	10,784	10,784	10,784	10,784	10,784	10,784
Panel C: Districts with 10-90% Assignment Rate, 5% Common Support Restriction								
Treatment × Post	216.922***	4.269***	3.419***	0.012	-0.026**	-0.072**	0.002	0.003
	(6.768)	(0.393)	(0.318)	(0.010)	(0.011)	(0.032)	(0.009)	(0.033)
Observations	9,544	9,544	9,544	9,544	9,544	9,544	9,544	9,544
Panel D: Districts with 15-85% Assignment Rate, Minimal Common Support Restriction								
Treatment × Post	222.273***	4.790***	3.963***	0.015	-0.025**	-0.074**	-0.001	-0.004
	(7.020)	(0.421)	(0.340)	(0.011)	(0.011)	(0.032)	(0.009)	(0.034)
Observations	9,488	9,488	9,488	9,488	9,488	9,488	9,488	9,488
Panel E: Districts with 15-85% Assignment Rate, 1% Common Support Restriction								
Treatment × Post	221.829***	4.697***	3.876***	0.017	-0.026**	-0.075**	0.002	0.005
	(7.096)	(0.426)	(0.341)	(0.011)	(0.010)	(0.032)	(0.009)	(0.034)
Observations	9,272	9,272	9,272	9,272	9,272	9,272	9,272	9,272
Panel F: Districts with 15-85% Assignment Rate, 2.5% Common Support Restriction								
Treatment × Post	221.829***	4.697***	3.876***	0.017	-0.026**	-0.075**	0.002	0.005
	(7.096)	(0.426)	(0.341)	(0.011)	(0.010)	(0.032)	(0.009)	(0.034)
Observations	9,272	9,272	9,272	9,272	9,272	9,272	9,272	9,272
Panel G: Districts with 15-85% Assignment Rate, 5% Common Support Restriction								
Treatment × Post	220.095***	4.290***	3.548***	0.015	-0.025**	-0.067**	0.005	0.018
	(7.225)	(0.431)	(0.342)	(0.012)	(0.011)	(0.031)	(0.010)	(0.035)
Observations	8,150	8,150	8,150	8,150	8,150	8,150	8,150	8,150

Notes: This table shows the effects of CHOs on healthcare services and health outcomes for different sample restrictions. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table A9: Effects of Community Health Officers on Alternative Top-Coding Strategies

	Elderly (56+) Mortality			Infant Mortality		
	Number of Deaths (1)	Mortality Rate (2)	Mortality Rate (IHS) (3)	Number of Deaths (4)	Mortality Rate (5)	Mortality Rate (IHS) (6)
Panel A: No Top-Coding						
Treatment × Post	-0.080*	8.043	-0.081**	0.003	0.002	-0.018
	(0.043)	(6.347)	(0.037)	(0.015)	(0.311)	(0.034)
Control Group Mean (Pre-Periods)	0.743	25.061	0.732	0.186	2.985	0.479
Treatment Group Mean (Pre-Periods)	0.775	8.105	0.752	0.184	2.878	0.475
Counterfactual Treatment Group Mean (Post-Periods)	0.704	1.917	0.778	0.200	3.125	0.529
Observations	10,190	10,190	10,190	10,190	10,190	10,190
Panel B: Top-Coding 97.5%						
Treatment × Post	-0.079**	-0.312*	-0.090***	-0.006	-0.161	-0.018
	(0.035)	(0.166)	(0.034)	(0.012)	(0.211)	(0.033)
Control Group Mean (Pre-Periods)	0.650	2.789	0.699	0.167	2.498	0.470
Treatment Group Mean (Pre-Periods)	0.687	2.800	0.735	0.169	2.483	0.467
Counterfactual Treatment Group Mean (Post-Periods)	0.677	2.764	0.771	0.187	2.815	0.521
Observations	10,190	10,190	10,190	10,190	10,190	10,190
Panel C: Top-Coding 95%						
Treatment × Post	-0.074**	-0.284**	-0.088***	-0.004	-0.108	-0.016
	(0.030)	(0.136)	(0.033)	(0.009)	(0.168)	(0.032)
Control Group Mean (Pre-Periods)	0.569	2.463	0.683	0.134	2.188	0.458
Treatment Group Mean (Pre-Periods)	0.609	2.516	0.721	0.133	2.169	0.455
Counterfactual Treatment Group Mean (Post-Periods)	0.622	2.547	0.761	0.148	2.442	0.507
Observations	10,190	10,190	10,190	10,190	10,190	10,190

Notes: This table shows the effects of CHOs on healthcare services and health outcomes for alternative top-coding strategies. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. The sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table A10: Alternative Weighting

	Number of Patient Visits	Number of Hypertension Patient Visits	Number of Diabetes Patient Visits	Maternal & Child Health Services Index	Any Elderly Death	Elderly Mortality Rate (IHS)	Any Infant Death	Infant Mortality Rate (IHS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Propensity Scores using LASSO								
Treatment × Post	217.494***	4.546***	3.558***	0.013	-0.022**	-0.057**	0.000	-0.001
	(7.871)	(0.377)	(0.306)	(0.011)	(0.009)	(0.029)	(0.009)	(0.031)
Control Group Mean (Pre-Periods)	252.197	4.373	3.722	0.065	0.242	0.721	0.133	0.470
Treatment Group Mean (Pre-Periods)	243.761	3.913	3.330	0.047	0.256	0.743	0.133	0.472
Counterfactual Treatment Group Mean (Post-Periods)	314.319	6.144	5.354	0.147	0.266	0.743	0.144	0.509
Observations	10,190	10,190	10,190	10,190	10,190	10,190	10,190	10,190
Panel B: Entropy Balancing								
Treatment × Post	221.628***	4.646***	3.622***	0.013	-0.020**	-0.053*	0.001	0.001
	(7.234)	(0.355)	(0.296)	(0.011)	(0.010)	(0.029)	(0.008)	(0.030)
Control Group Mean (Pre-Periods)	245.291	4.204	3.564	0.025	0.238	0.713	0.129	0.459
Treatment Group Mean (Pre-Periods)	243.761	3.913	3.330	0.047	0.256	0.743	0.133	0.472
Counterfactual Treatment Group Mean (Post-Periods)	310.185	6.044	5.290	0.146	0.264	0.739	0.143	0.507
Observations	10,190	10,190	10,190	10,190	10,190	10,190	10,190	10,190

Notes: This table shows the effects of CHOs on healthcare services and health outcomes for alternative top-coding strategies. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. In Panel A, subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores estimated based on a lasso regression that uses all the covariates listed in Table 1. In Panel B, subcenter-level weights for the control group are constructed by entropy balancing using the first-order moments of the following variables: distance to the district HQ, distance to the subdistrict HQ, and district fixed effects. The sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table A11: Alternative Difference-in-Differences Estimators

	Number of Patient Visits	Number of Hypertension Patient Visits	Number of Diabetes Patient Visits	Maternal & Child Health Services Index	Any Elderly Death	Elderly Mortality Rate (IHS)	Any Infant Death	Infant Mortality Rate (IHS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Subcenter-Specific Linear Trends								
Treatment × Post	163.480***	3.167***	2.474***	-0.008	-0.036*	-0.120**	-0.022	-0.080
	(8.509)	(0.480)	(0.344)	(0.018)	(0.019)	(0.054)	(0.024)	(0.095)
Control Group Mean (Pre-Periods)	244.221	4.035	3.383	0.019	0.237	0.707	0.134	0.475
Treatment Group Mean (Pre-Periods)	243.761	3.913	3.330	0.047	0.256	0.743	0.133	0.472
Counterfactual Treatment Group Mean (Post-Periods)	368.333	7.523	6.438	0.168	0.281	0.806	0.166	0.588
Observations	40,760	40,760	40,760	40,760	40,760	40,760	40,760	40,760
Panel B: Double-Robust Estimator								
Treatment × Post	215.901***	4.287***	3.440***	0.010	-0.029***	-0.083***	-0.003	-0.016
	(6.425)	(0.357)	(0.294)	(0.010)	(0.010)	(0.029)	(0.009)	(0.031)
Control Group Mean (Pre-Periods)	244.221	4.035	3.383	0.019	0.237	0.707	0.134	0.475
Treatment Group Mean (Pre-Periods)	243.761	3.913	3.330	0.047	0.256	0.743	0.133	0.472
Counterfactual Treatment Group Mean (Post-Periods)	315.912	6.403	5.472	0.149	0.274	0.770	0.147	0.524
Observations	10,190	10,190	10,190	10,190	10,190	10,190	10,190	10,190

Notes: This table shows the effects of CHOs on healthcare services and health outcomes for alternative difference-in-differences estimators. In Panel A, the regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy, year and subcenter fixed effects, and an interaction between linear time trends and subcenter fixed effects. In Panel B, the regression coefficients are estimated using the double robust estimator proposed by Sant'Anna and Zhao (2020). The sample period covers Q2 2021 until Q1 2023. While the sample in Panel A consists of subcenter-quarter observations, the sample in Panel is aggregated at the subcenters-pre/post level. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table A12: Alternative Empirical Strategy Based on Closest Subcenter

	Number of Patient Visits	Number of Hypertension Patient Visits	Number of Diabetes Patient Visits	Maternal & Child Health Services Index	Any Elderly Death	Elderly Mortality Rate (IHS)	Any Infant Death	Infant Mortality Rate (IHS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post	219.566***	4.571***	3.624***	0.019	-0.028*	-0.081*	0.002	0.004
	(8.220)	(0.481)	(0.429)	(0.014)	(0.016)	(0.047)	(0.012)	(0.043)
Control Group Mean (Pre-Periods)	257.406	3.940	3.197	-0.042	0.257	0.766	0.134	0.482
Treatment Group Mean (Pre-Periods)	244.506	3.877	3.309	0.050	0.257	0.747	0.133	0.469
Counterfactual Treatment Group Mean (Post-Periods)	313.989	6.485	5.671	0.139	0.274	0.775	0.140	0.497
Observations	11,494	11,494	11,494	11,494	11,494	11,494	11,494	11,494

Notes: This table shows the effects of CHOs on healthcare services and health outcomes. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and year and subcenter fixed effects. Standard errors are clustered at the subcenter level. Each treatment subcenter is matched to the closest control subcenters (with replacement). The sample consists of 5,747 subcenters and the sample period covers Q2 2021 until Q1 2023. Outcomes are obtained from the Pregnancy, Child Tracking and Health Services Management System.

Table A13: Effects on Healthcare Services at Physician-Staffed Public Clinics

	Number of Patient Visits (IHS)	Number of Hypertension Patients (IHS)		Number of Diabetes Patients (IHS)	
		Diagnosed	On Treatment	Diagnosed	On Treatment
	(1)	(2)	(3)	(4)	(5)
Treatment Share $\geq$ 50% $\times$ Post	0.136	0.175*	0.231**	0.168	0.084
	(0.281)	(0.103)	(0.116)	(0.110)	(0.097)
Control Group Mean (Q1 2022)	8.111	2.056	3.371	2.905	1.672
Treatment Group Mean (Q1 2022)					
Counterfactual Treatment Group Mean (Post-Periods)	-0.136	-0.175	-0.231	-0.168	-0.084
Observations	960	960	960	960	960

Notes: This table shows the effects of CHOs on healthcare services at public clinics. The regression coefficients are estimated by regressing the outcome on interactions between an indicator variable for whether at least 50% of the linked subcenters received a CHO (weighted by population) and the post-periods dummy and year and subcenter fixed effects. Standard errors are clustered at the public clinic level. Clinic-level weights for the control group are constructed by inverse probability weighting using propensity scores based on district fixed effects. The sample consists of 480 public clinic and the sample period covers Q2 2021 until Q4 2022. Outcomes are obtained from the Health and Wellness Center Portal.

Table A14: Heterogeneity by Distance to Physician-Staffed Public Clinic

	Number of Patient Visits	Number of Hypertension Patient Visits	Number of Diabetes Patient Visits	Maternal & Child Health Services Index	Any Elderly Death	Elderly Mortality Rate (IHS)	Any Infant Death	Infant Mortality Rate (IHS)	Any Hospi-talization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment × Post × Closest Distance Tercile	186.993***	3.677***	2.653***	-0.003	-0.034*	-0.086	0.006	0.015	-0.020
	(13.288)	(0.633)	(0.555)	(0.020)	(0.019)	(0.057)	(0.015)	(0.055)	(0.016)
Treatment × Post × Middle Distance Tercile	238.136***	3.896***	3.754***	0.016	0.004	-0.003	-0.001	-0.013	-0.014
	(14.908)	(1.003)	(0.725)	(0.019)	(0.016)	(0.052)	(0.016)	(0.058)	(0.017)
Treatment × Post × Furthest Distance Tercile	222.786***	5.401***	3.949***	0.021	-0.067**	-0.195*	-0.018	-0.064	-0.008
	(11.906)	(0.531)	(0.428)	(0.019)	(0.030)	(0.100)	(0.019)	(0.075)	(0.015)
p-value: Closest = Middle	0.010	0.854	0.228	0.489	0.126	0.281	0.735	0.720	0.784
p-value: Closest = Furthest	0.045	0.037	0.064	0.384	0.363	0.346	0.311	0.394	0.562
p-value: Middle = Furthest	0.421	0.185	0.817	0.863	0.039	0.090	0.494	0.594	0.786
Closest Distance Tercile:									
Control Group Mean (Pre-Periods)	245.116	3.906	3.218	-0.045	0.273	0.828	0.153	0.543	0.021
Treatment Group Mean (Pre-Periods)	238.548	3.708	2.950	-0.017	0.274	0.801	0.144	0.516	0.043
Counterfactual Treatment Group Mean (Post-Periods)	335.484	6.895	6.025	0.087	0.298	0.835	0.148	0.533	0.037
Observations	3,398	3,398	3,398	3,398	3,398	3,398	3,398	3,398	1,992
Middle Distance Tercile:									
Control Group Mean (Pre-Periods)	257.724	4.110	3.604	0.082	0.243	0.712	0.139	0.486	0.027
Treatment Group Mean (Pre-Periods)	240.818	3.819	3.356	0.086	0.264	0.767	0.136	0.478	0.028
Counterfactual Treatment Group Mean (Post-Periods)	307.284	6.815	5.430	0.190	0.260	0.743	0.151	0.533	0.028
Observations	3,396	3,396	3,396	3,396	3,396	3,396	3,396	3,396	1,931
Furthest Distance Tercile:									
Control Group Mean (Pre-Periods)	227.845	4.100	3.323	0.024	0.190	0.562	0.107	0.384	0.026
Treatment Group Mean (Pre-Periods)	253.600	4.276	3.783	0.086	0.225	0.642	0.117	0.409	0.035
Counterfactual Treatment Group Mean (Post-Periods)	305.753	5.415	4.957	0.182	0.265	0.741	0.144	0.509	0.025
Observations	3,396	3,396	3,396	3,396	3,396	3,396	3,396	3,396	1,961

Notes: This table shows the effects of CHOs on healthcare services and health outcomes by distance to the public clinic. We regress the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them, separately for subcenters in each distance tercile. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample consists of 5,095 subcenters. In columns 1-8, the outcomes are at the subcenter level and are obtained from the Pregnancy, Child Tracking and Health Services Management System. The outcome in column 9 is at the household member level and is obtained from our household surveys.

Table A15: Heterogeneity by Subcenter Infrastructure

	Number of Patient Visits	Number of Hypertension Patient Visits	Number of Diabetes Patient Visits	Maternal & Child Health Services Index	Any Elderly Death	Elderly Mortality Rate (IHS)	Any Infant Death	Infant Mortality Rate (IHS)	Any Hospi-talization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment × Post × Electricity	199.657***	2.293***	2.321***	-0.050	-0.109*	-0.359**	-0.021	-0.095	-0.022**
	(24.842)	(0.805)	(0.652)	(0.044)	(0.064)	(0.154)	(0.078)	(0.391)	(0.009)
Treatment × Post × No Electricity	257.451***	1.533	2.159**	-0.022	0.113	0.199	-0.074	-0.137	-0.008
	(36.024)	(0.959)	(1.060)	(0.080)	(0.073)	(0.134)	(0.066)	(0.334)	(0.010)
p-value: Coef 1 = Coef 2	0.188	0.545	0.896	0.758	0.023	0.007	0.605	0.936	0.034
Subcenter with Electricity:									
Control Group Mean (Pre-Periods)	233.893	2.860	2.525	-0.056	0.170	0.424	0.232	1.189	0.023
Treatment Group Mean (Pre-Periods)	269.871	3.565	2.581	0.084	0.222	0.614	0.190	0.953	0.033
Counterfactual Treatment Group Mean (Post-Periods)	288.157	4.167	2.812	0.192	0.275	0.772	0.178	0.868	0.033
Observations	254	254	254	254	254	254	254	254	4,062
Subcenter with No Electricity:									
Control Group Mean (Pre-Periods)	232.920	4.422	3.073	0.012	0.236	0.512	0.110	0.563	0.025
Treatment Group Mean (Pre-Periods)	189.980	5.236	3.858	0.225	0.169	0.433	0.196	0.954	0.042
Counterfactual Treatment Group Mean (Post-Periods)	182.597	5.365	4.672	0.256	0.043	0.201	0.256	1.068	0.033
Observations	132	132	132	132	132	132	132	132	1,822

Notes: This table shows the effects of CHOs on healthcare services and health outcomes by whether a subcenter had electricity at baseline. We regress the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them, separately for subcenters with and without electricity. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample consists of 193 subcenters. In columns 1-8, the outcomes are at the subcenter level and are obtained from the Pregnancy, Child Tracking and Health Services Management System. The outcome in column 9 is at the household member level and is obtained from our household surveys.

Table A16: Effects of Community Health Officers on Subcenter Characteristics

	Number of Providers	Highest Degree is 3+ Years	Number of Community Health Workers	Electricity	Equipment Index	Medicine Index
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	0.995***	0.954***	-0.070	0.022	-0.172	-0.223
	(0.025)	(0.024)	(0.122)	(0.057)	(0.417)	(0.346)
Control Group Mean (Pre-Period)	1.000	0.038	2.615	0.588	7.417	3.848
Treatment Group Mean (Pre-Period)	1.011	0.053	2.947	0.628	7.484	3.661
Counterfactual Treatment Group Mean (Post-Period)	1.035	0.046	2.998	0.665	6.860	4.078
Observations	378	378	376	374	282	282

Notes: This table shows the effects of CHOs on subcenter labor force and infrastructure We regress the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample consists of 193 subcenters. Outcomes are obtained from surveys with ANMs and CHOs.

Table A17: Patient Characteristics in Exit Surveys

	Female	Scheduled Caste	Scheduled Tribe	First Time to Subcenter
	(1)	(2)	(3)	(4)
Treatment	0.021	0.091**	0.007	0.122***
	(0.091)	(0.037)	(0.100)	(0.044)
Control Group Mean	0.537	0.000	0.199	0.017
Observations	177	177	177	174

Notes: This table shows the effects of CHOs on patient characteristics according to patient exit survey. In each column, we regress the outcome on an indicator variable for whether a CHO was assigned to the subcenter in March 2022. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample consists of 177 patients who visited the subcenter for outpatient care services.

Table A18: Heterogeneity by CHO Quality

	Number of Patient Visits	Number of Hypertension Patient Visits	Number of Diabetes Patient Visits	Maternal & Child Health Services Index	Any Elderly Death	Elderly Mortality Rate (IHS)	Any Infant Death	Infant Mortality Rate (IHS)	Any Hospi-talization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Heterogeneity by Official Merit Score									
Treatment × Post × High-Merit CHOs	219.979***	4.274***	3.388***	0.024*	-0.028**	-0.086*	-0.005	-0.024	-0.016**
	(9.158)	(0.513)	(0.401)	(0.013)	(0.014)	(0.044)	(0.011)	(0.041)	(0.007)
Treatment × Post × Low-Merit CHOs	218.426***	4.244***	3.529***	-0.006	-0.034**	-0.093**	-0.001	-0.007	-0.008
	(9.358)	(0.540)	(0.422)	(0.013)	(0.014)	(0.045)	(0.011)	(0.041)	(0.007)
p-value: Coef 1 = Coef 2	0.868	0.954	0.737	0.014	0.613	0.802	0.654	0.646	0.271
Observations	9,602	9,602	9,602	9,602	9,602	9,602	9,602	9,602	5,850
Panel B: Heterogeneity by Survey Vignette Performance									
Treatment × Post × High-Vignette-Perf. CHOs	196.897***	1.359	1.877**	-0.032	-0.039	-0.160	-0.047	-0.139	-0.018**
	(31.987)	(0.889)	(0.834)	(0.045)	(0.059)	(0.135)	(0.056)	(0.277)	(0.008)
Treatment × Post × Low-Vignette-Perf. CHOs	198.222***	1.856**	1.841***	-0.020	0.004	-0.091	-0.020	-0.026	-0.010
	(29.274)	(0.833)	(0.704)	(0.055)	(0.052)	(0.120)	(0.057)	(0.286)	(0.009)
p-value: Coef 1 = Coef 2	0.970	0.669	0.972	0.858	0.414	0.622	0.600	0.669	0.233
Observations	386	386	386	386	386	384	386	386	5,850

Notes: This table shows the effects of CHOs on healthcare services and health outcomes by CHO quality. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and CHO quality, while controlling for year and subcenter fixed effects. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. In Panel A, the sample consists of 4,801 subcenters and CHO quality is measured based on the ranking of CHOs in screening exams. In Panel B, the sample consists of 193 subcenters and CHO quality is measured based on the average performance across two medical vignettes in provider surveys. In columns 1-8, the outcomes are at the subcenter level and are obtained from the Pregnancy, Child Tracking and Health Services Management System. The outcome in column 9 is at the household member level and is obtained from our household surveys.

Table A19: Effects of Community Health Officers on Other Private Provider Outcomes

	Number of Providers	Injection Rate	Antibiotics Prescription Rate
	(1)	(2)	(3)
Treatment × Post	0.155	-0.032	0.012
	(0.099)	(0.058)	(0.077)
Control Group Mean (Baseline)	1.446	0.213	0.387
Treatment Group Mean (Baseline)	1.092	0.207	0.343
Counterfactual Treatment Group Mean (Endline)	0.967	0.310	0.360
Observations	384	364	361

Notes: This table shows the effects of CHOs on the number of private providers in the catchment area and the use of potentially harmful behavior in the private sector. We regress the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The regressions are run at the subcenter level in column 1 and at the provider level in column 2-3.

Table A20: Effects of Community Health Officers on Private Provider Quality Index Components

	Number of Co-Workers	Number of Training Workshops Attended (Past 6 Months)	Currently Enrolled in a Degree Program	Number of Medicines in Stock	Checklist Completion Rate (Vignette)
	(1)	(2)	(3)	(4)	(5)
Panel A: Pooled					
Treatment × Post	0.056	0.447*	0.156**	-4.925	0.178
	(0.060)	(0.242)	(0.067)	(4.304)	(0.169)
Control Group Mean (Pre-Period)	1.052	0.527	0.195	10.787	-0.002
Treatment Group Mean (Pre-Period)	1.159	0.493	0.072	19.403	-0.025
Counterfactual Treatment Group Mean (Post-Periods)	1.211	0.205	-0.032	30.189	-0.458
Observations	471	427	473	417	342
Panel B: Heterogeneity by Distance					
Treatment × Post × Close Providers	0.126*	0.674**	0.182*	-1.287	0.190
	(0.069)	(0.317)	(0.097)	(4.505)	(0.208)
Treatment × Post × Distant Providers	-0.012	-0.014	0.111	-13.408	0.278
	(0.113)	(0.345)	(0.102)	(9.095)	(0.291)
p-value: Coef 1 = Coef 2	0.306	0.137	0.633	0.231	0.805
Close Providers:					
Control Group Mean (Baseline)	1.083	0.625	0.192	9.408	0.033
Treatment Group Mean (Baseline)	1.040	0.432	0.078	16.500	-0.031
Counterfactual Treatment Group Mean (Endline)	1.072	0.016	-0.014	27.235	-0.421
Observations	308	284	310	277	224
Distant Providers:					
Control Group Mean (Baseline)	1.000	0.350	0.199	13.419	-0.058
Treatment Group Mean (Baseline)	1.344	0.609	0.062	24.538	-0.013
Counterfactual Treatment Group Mean (Endline)	1.415	0.591	-0.073	37.304	-0.662
Observations	163	143	163	140	118

Notes: This table shows the effects of CHOs on the components of the private provider quality index. In Panel A, we regress the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them. In Panel B, we regress the outcome on the treatment dummy, the post-period dummy, and an interaction between both of them, separately for distant and close providers. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments and health and wellness center conversion. See Section 3.2 for details. The sample pools the baseline survey round and two endline survey rounds. We define close providers as private providers that are not more than 500 meters away from the subcenter building.

Table A21: Heterogeneity by CHO Gender

	Number of Patient Visits	Number of Hypertension Patient Visits	Number of Diabetes Patient Visits	Maternal & Child Health Services Index	Any Elderly Death	Elderly Mortality Rate (IHS)	Any Infant Death	Infant Mortality Rate (IHS)	Any Hospitalization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment × Post × Female CHOs	198.129***	3.822***	3.123***	0.018	-0.027*	-0.073	-0.013	-0.053	-0.014
	(9.599)	(0.539)	(0.426)	(0.014)	(0.015)	(0.046)	(0.012)	(0.043)	(0.009)
Treatment × Post × Male CHOs	224.899***	4.536***	3.592***	0.006	-0.034**	-0.101**	0.001	-0.004	-0.020**
	(8.548)	(0.489)	(0.380)	(0.012)	(0.013)	(0.043)	(0.010)	(0.038)	(0.009)
p-value: Coef 1 = Coef 2	0.003	0.155	0.248	0.324	0.536	0.379	0.161	0.176	0.323
Control Group Mean (Pre-Periods)	244.221	4.035	3.383	0.019	0.237	0.707	0.134	0.475	0.024
Treatment Group Mean (Female CHOs, Pre-Periods)	244.248	3.726	3.319	0.048	0.249	0.721	0.143	0.506	0.034
Treatment Group Mean (Male CHOs, Pre-Periods)	244.543	3.991	3.312	0.052	0.261	0.758	0.130	0.458	0.038
Observations	10,156	10,156	10,156	10,156	10,156	10,156	10,156	10,156	5,850

Notes: This table shows the effects of CHOs on healthcare services and health outcomes by CHO gender. The regression coefficients are estimated by regressing the outcome on interactions between the CHO assignment dummy and the post-periods dummy and CHO gender, while controlling for year and subcenter fixed effects. Standard errors are clustered at the subcenter level. Subcenter-level weights for the control group are constructed by inverse probability weighting using propensity scores based on inputs used for CHO assignments. See Section 3.2 for details. In columns 1-8, the sample consists of 5,078 subcenters and the sample period covers Q2 2021 until Q1 2023. In these columns, the outcomes are at the subcenter level and are obtained from the Pregnancy, Child Tracking and Health Services Management System. The outcome in column 9 is at the household member level and is obtained from our household surveys.