Explaining the Evolving Demand for Healthcare in Rural China 2011-2018: A Non-linear Decomposition Approach

Yunwei Chen[1], Sean Sylvia[1], Paiou Wu[2], Hongmei Yi[2]

[1] Department of Health Policy and Management, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, USA

[2] School of Advanced Agricultural Sciences, Peking University, Beijing, China

December 4, 2020

ABSTRACT

With a goal of reducing patient loads at upper-level health facilities, reforms of China's health system over the past decade have aimed to strengthen primary care in lower-level clinics and health centers. This paper studies the changes in rural patient demand for health services across tiers of China's rural health system using longitudinal and nationally-representative data spanning 2011 to 2018. Despite policy goals, we document a continued large-scale shift in utilization from lower-level facilities to upper-level hospitals. We estimate that between 2011 and 2018, village clinic utilization dropped by 35% while the utilization of outpatient services in county hospitals increased by 78%. Non-linear decompositions show that structural changes in the patient, provider, and community factors accounted for more than half of the decrease in the demand for health services at the village level. The changing disease pattern shifting towards chronic diseases, along with the decreased availability of medical resources at village clinics, were the strongest contributors to the demand shift.

KEYWORDS

healthcare-seeking behavior, demand for healthcare, decomposition, rural health, health reform, bypassing, China

1. INTRODUCTION

Over the past decade, China has implemented wide-ranging health reforms with the goal of improving the quality of healthcare and addressing sources of inefficiency in its health system (Chen, 2009; Yip *et al.*, 2012, 2019). One challenge that these reforms have aimed to address is that, without gatekeeping, patients frequently bypass local primary care providers and seek services directly in higher-level hospitals (Eggleston *et al.*, 2008; Hsiao, 1995). This phenomenon is believed to be a source of significant inefficiencies in healthcare delivery as it contributes to overcrowding in higher-tiered hospitals and underutilization of primary care at lower-level facilities. While reforms have included numerous initiatives to promote greater use of grassroots facilities – such as increased resources targeted to grassroots providers and policy encouragement of an integrated and tiered healthcare delivery system – the extent of changes in bypassing and factors affecting healthcare-seeking across health system tiers remains underexplored empirically.

In this paper, we examine the changes in bypassing and healthcare-seeking behavior in rural areas of China using longitudinal and nationally-representative data spanning 2011 to 2018. We model healthcare-seeking behavior using the patient choice of healthcare providers within China's rural health system and start by showing the changes in patient utilization of service tiers (village, township, county, and city-level facilities) over the past decade. We then link healthcare-seeking to detailed data on primary healthcare providers and local communities to present how different demand and supply-side factors explain variation in healthcare-seeking over time. Lastly, using the non-linear decomposition (Fairlie, 1999, 2005), we decompose the changes in patient demand for health services over time and examine how structural changes in demographic factors, disease burden, community-level healthcare access, and local provider characteristics have contributed to changes in the facility choice over time. While these factors have generally been proposed as determinants of patient demand for healthcare, examining the relative contributions of these factors to the observed demand change in the past decade provides evidence for future policy responses.

We find a dramatic change in the patient choice of healthcare providers in rural China from 2011 to 2018. Conditional on being ill and seeking health services in the health system, village clinic utilization decreased by 18.7 percentage points from 52.7% in 2011 to 34.0% in 2018. At the same time, rural patient choices of township health centers, county hospitals, and hospitals outside of the county have increased accordingly, with the county hospitals observing the biggest increase. Rural county hospitals, rather than city-level hospitals, have absorbed most of the increase in the bypassing activities from rural residents. Structural changes in the patient, provider, and community factors accounted for more than half of the decrease in the demand for health services at the village level. The changing disease pattern shifting towards chronic diseases explains the largest portion of the demand change, followed by the decreased availability of medical resources at village clinics. This finding seemingly contradicts the initial intention of the healthcare reform plan launched in 2009, which has emphasized the development of health infrastructure at the grassroots level and movement toward a gatekeeping system by improving the ability of lower-level facilities to manage a growing burden of chronic non-communicable diseases (Chen, 2009).

This study builds on previous literature in China and other low and middle-income countries on patient choice of healthcare providers. One strand of research has focused on identifying the determinants of how patients select facilities for health services (Akin & Hutchinson, 1999; Gauthier & Wane, 2011; Leonard, Mliga, & Haile Mariam, 2002; Liu *et al.*, 2018; Qian *et al.*, 2010; Qian *et al.*, 2009; Yang *et al.*, 2014; Yip, Wang, & Liu, 1998). These studies suggest that patient choice for healthcare is associated with various factors, including patient, provider, and context characteristics. While patient characteristics, such as age, income, and education, are the most reported in the literature, these factors have generally been found to be poor predictors of healthcare seeking. Provider-side factors, however, such as the availability of drugs and medical equipment at lower-level facilities, have proven more predictive of patient facility choices (Liu *et al.*, 2018). Similar trends have been observed in other developing countries without gatekeeping-based systems, where bypassing is a common phenomenon. Akin and Hutchinson (1999) suggested that bypassing in Sir Lanka signaled significant problems with the quality of care at bypassed facilities. Even health services free of charge and in close proximity will not attract patients if the quality of healthcare is low. Similarly, Leonard and colleagues (2002) found that patients seek facilities staffed by more knowledgeable physicians and stocked with better medical supplies in Tanzania.

Our findings are also relevant to a second strand of research evaluating the impact of policy interventions on demand for health care, especially healthcare reforms in China (e.g. Brown & Theoharides, 2009; Yu *et al.*, 2010; Zhang *et al.*, 2014). These studies have found that reimbursement from the public health insurance expansion has made higher-level facilities more affordable, pushing people away from primary care in lower-level facilities. However, empirical evidence on the impacts of other reform interventions on patient choices, such as primary care strengthening, has been scarce, likely due to the complexity of policy interventions and the difficulty in estimating the causal effects of interventions applied across the entire country (Powell-Jackson, Yip, & Han, 2015).

We contribute to this literature in two ways. First, we use a nationally-representative panel survey of rural communities in China to explore how the patient choice of healthcare provider has changed between 2011 and 2018. We build on previous studies of patient facility choice that have largely used cross-sectional data and local samples. Second, we analyze these dynamics by decomposing changes in factors associated with patient utilization of village clinics over time in two separate phases. This decomposition allows us to quantify the contributions of structural changes in demographic, provider, and community factors in shaping the demand change for health services in the context of China's roll-out of health reforms.

2. INSTITUTIONAL BACKGROUND

The rural health delivery system in China operates in a three-tiered structure: village clinics, township health centers, and county hospitals. County hospitals refer the most serious illness to city hospitals in the urban sector (Yip *et al.*, 2010). In the rural sector, village clinics serve village populations and provide preventive and primary care. Township health centers, as the middle level, supervise village clinics while providing both curative and primary care. County hospitals, as the highest level of the rural health system, serve as referral centers for township and village but also provide primary care services. (Hsiao, 1995; Yip *et al.*, 1998). The county hospitals and township health centers are usually publicly owned. In 2016, 99% of township health centers were publicly owned, while 63% of village clinics were formally publicly owned (Li *et al.*, 2017).

Doctors working at the county hospitals and township health centers typically have passed the National Practicing Doctor (or Assistance Doctor) Examination and register as either licensed doctors or licensed assistant doctors after at least three years of formal medical training.[1] Meanwhile, village doctors – often former barefoot doctors, village workers, and traditional practitioners – may practice with a village doctor certificate. Local health authorities permit village doctors to obtain a village doctor certificate (rather than a regular license) to practice only in local village clinics if they have technical school education or have more than 20 years of practice experience (Anand *et al.*, 2008; Li *et al.*, 2017). While some village doctors have passed the National Practicing Doctor (or Assistance Doctor) Examination and are registered as licensed doctors, some are unlicensed and uncertified.

There is no strict gatekeeping mechanism in China. The general population is free to access any level of health care facilities. Consequently, patients may bypass primary care facilities and go directly to higher-tiered (and more) expensive hospitals even for minor conditions. Allowing for free patient choice may be better for population health given the poor quality of care at lower tiers of the health system (Guo *et al.*, 2020; Li *et al.*, 2020; Sylvia *et al.*, 2015, 2017); however, unnecessary bypassing has long been of concern to the government as it drives high costs and leads to overcrowding in the higher-tiered hospitals. Patient visits to large hospitals in China have been characterized by the "three longs and one short" phenomenon: long waiting times for registration, long waiting times to be billed, long waiting times for doctor appointments, and short consultation times with doctors (Chao *et al.*, 2017). In addition to undermining health system efficiency, this phenomenon has also been blamed as a source of frustration with the health system and even violence against healthcare providers (Hesketh *et al.*, 2012). Cai and colleagues (2019) investigated 459 criminal cases involving hospital violence

[1] Li *et al*. (2017) provide a detailed description of doctor training and qualification in China: "There are three levels of formal medical training: medical college (five years of medical education after 12 years of primary and secondary education to get a bachelor's degree of medicine); junior medical college (three years of medical education after 12 years of primary and secondary education); and technical school (three years of medical education after nine years of primary and secondary education). Completion of medical college is required to become a licensed doctor and junior medical college training is required to become a licensed assistant doctor."

between 2013 to 2016. They found that violent perpetrators were primarily male farmers, with the long waiting time reporting as one of the primary reasons.

While the bypassing phenomenon has imposed substantial pressure on hospitals in urban sectors, the rural health system also faces amplified challenges to efficiency due to rapid rural-urban migration and widening urban-rural inequality in access to quality health services. On the one hand, Rural-to-urban migration has largely left behind the elderly, the weak, and the sick in rural areas (Hu, Cook, & Salazar, 2008), implying greater demand for health services per population. On the other hand, rural areas have shown significant inadequacy in doctor density and competency (Anand *et al.*, 2008).

To address these issues, China announced wide-ranging reforms in 2009 (Chen, 2009). The five major targets of the health reform – a primary-care based integrated delivery system, a basic public health service program, a government-instituted universal health insurance coverage, a national essential drug system, and the reform of public hospital – have been designed to jointly address the health system inefficiency, the unaffordable medical expenses, and the growing inequalities in access to health care between rural and urban areas (Yip *et al.*, 2012, 2019). With "improving primary health care services through a renewed system of grassroots providers" identified as one of five key reform priorities, the government has made significant investments into primary healthcare institutions. Between 2008 and 2015, government subsidies to primary healthcare institutions increased from ¥19 billion (US$2.8 billion) to ¥140 billion ($20.3 billion) (Li *et al.*, 2017). In 2015, the government issued guidelines for operationalizing a tiered healthcare delivery system, encouraging coordinated and integrated care across levels (Yip *et al.*, 2019). In 2016, the government launched a "family doctor contract system" where residents could register for a family doctor team for primary care services, though demand has been low and few primary health providers are qualified as gatekeepers to provide high-quality services (Fu *et al.*, 2020; Yip *et al.*, 2019).

Although these policies have aimed to strengthen primary care and direct patient flow towards the lower-tiered facilities, there is a lack of quantitative evidence of how rural patient healthcare-seeking has changed in response to these policies at a national scale. Whether reforms have led to greater utilization of lower-level facilities is unclear. First, while reforms increased government funding for primary care, these investments in resources and infrastructure at the grassroots level may not translate into effective services and may not attract patients. Evidence from recent studies suggests significant deficits in the quality of care delivered in rural clinics and health centers (Guo *et al.*, 2020; Li *et al.*, 2020; Sylvia *et al.*, 2015, 2017). Rising wealth and expanding health insurance coverage may have had a countervailing effect by stimulating demand for the higher quality services, leading patients to seek care at high-tiered hospitals where perceived quality of care is higher. Second, population aging and a shifting disease burden toward non-communicable diseases may have had important effects on patient utilization patterns across health system tiers, though the direction of these effects is not clear (Yang *et al.*, 2008). On one hand, allocating greater resources to primary care may have improved the capacity of grassroots facilities to detect and treat non-communicable diseases. Indeed, the government has provided supply-side subsidies to primary care providers to deliver basic public health services for the population in their catchment areas, with the management of non-communicable diseases as one of their main responsibilities (Yip *et al.*, 2012, 2019). On the other hand, increased public health duties of village clinicians may have reduced their provision of curative care, pushing patients to seek treatment at high-tiered facilities. Ding *et al.* (2013) investigated village doctors' experience of delivering public health services and reported that the significant time investment required to perform public health duties may have negatively impacted medical service provision.

3. DATA

3.1. Study setting

We use data from the China Rural Development Survey (CRDS), a nationally-representative survey of rural residents and infrastructure conducted by the Chinese Academy of Sciences and Peking University. The CRDS survey was first conducted in 2005, which surveyed a random sample of 100 villages from 25 rural counties across five Chinese provinces of Jiangsu, Sichuan, Shaanxi, Jilin, and Hebei. To ensure the sample was nationally-representative, the research team chose five provinces in 2005 to represent each of China's major agricultural and ecological zones: Jiangsu in the low lying south-eastern coastal regions, Sichuan in the poor south-western mountainous region, Shaanxi in the north-western arid region, Jilin in the north-eastern temperate region, and Hebei in the northern plain region. Five counties were selected within each province with each representing one of five strata of per capita income. Two townships from each county were randomly selected with one from the top and one from the bottom half of the distribution, and two villages from each township were chosen using the same sampling procedure (Babiarz *et al.*, 2010). The same 100 villages were followed up in 2008, 2012, 2016, and 2019. This paper includes datasets from the latest three waves in 2012, 2016, and 2019. We do not consider the previous waves because some survey modules differed, complicating comparisons.

3.2. Data collection

Teams of enumerators trained by the research team conducted surveys in all sampled villages for each wave. All three survey waves contain four components: a village module, a village clinic module, a village clinician module, and a household module.

Village, village clinic, and village clinician surveys. The CRDS surveyed village officials, village clinics, and village clinicians in all 100 sampled villages. The resulting sample includes 143, 122, and 124 village clinics, as well as 208, 162, and 152 village clinicians[2] surveyed in 2012, 2016, and 2019.

The village module collected information on the population and economic status of the village. The village clinic module gathered information on clinic infrastructure and workforce, including drug availability and variety, medical equipment, and the number of clinicians. Village clinicians were surveyed on their education, qualification, and medical practice.

Descriptive statistics on the village, village clinic, and village clinician data are in Table A1 in the Appendix. About 4-8% of villages reported having no village clinics. Most villages had only one village clinic: in 2011, 58% of villages had one village clinic, and this number increased to 75% in 2018. Both the total number of village clinics and clinicians have decreased across three waves: in 2011, 143 village clinics and 208 village clinicians were in the survey; however, only 124 village clinics and 152 village clinicians remained in the surveyed areas in 2018. The drug variety[3] available in village clinics also declined. In 2011, 246 drugs were available at village clinics on average, whereas the average number of drug varieties in inventory decreased to 171 in 2018. The majority of doctors were male with an average age of 48 to 52, having 25 to 30 medical practicing years on average. About 27% of clinicians had a middle

[2] Only village clinicians who provide curative care were surveyed.
[3] Drug variety is defined as the number of drugs in inventory by commercial names, including western drugs, Chinese patent drugs, and Chinese herbal drugs.

school or lower education in 2011, which decreased to 15% in 2018. About two-thirds of village clinicians practice medicine with a village doctor certificate, and 21-23% of clinicians were licensed (assistant) doctors. In 2011 and 2015, 4-6% of village doctors were neither licensed doctors nor certified village doctors, while this number decreased to zero in 2018.

Household survey. We link the data on villages and village providers to individuals living in the sampled villages. Within each sampled village, the CRDS used village rosters to randomly select eight households in each village during the first wave in 2005. The number of selected households increased to 20 households in each village during the second wave in 2008, and the same 20 households were revisited in later waves. When a household was lost to follow-up, it was replaced with a household from the same village using the same sampling procedure as above, keeping the total in the sample at 20 for that village. Some lost households were re-followed in later waves; therefore, it is possible to have more than 2000 households for each wave.[4] Household follow-up rates were 88.99% in 2016 and 89.47% in 2019. Appendix Table A2 shows that demographic and socioeconomic trends between followed and newly-added households in each wave were similar.

Household heads completed the survey, and information about all household members in every sampled household was collected. The household members include: (1) the head and spouse; (2) unmarried children of the head and spouse (including students, servicemen, and migrants not living at home); (3) married children but living with the head and spouse; and (4) other relatives living with the head and spouse for more than three months (including grandchildren, babysitters, and others). Household's size changed with births, marriages, and

[4] There were 2013 households in 2011, 2008 households in 2015, and 2003 households in 2018; Among them, 1546 households were followed in all three waves.

deaths over the years. A total of 9347, 8309, and 8936 individuals were surveyed in 2012, 2016, and 2019.

The household module gathered data on family assets, distance to health facilities, and every household member's demographic information and healthcare-seeking. The relevant questions include whether each household member was ill during the past year, whether the sick member consulted a doctor, the facility choice of the previous year's last illness, and the disease type diagnosed by doctors. Health facility choices included local village clinics, neighboring village clinics, township health centers, county hospitals, hospitals outside of the county, and others.

3.3. Variable definitions

To take advantage of available data on both the demand side from a household and village community survey and the supply side from a village clinic and clinician survey, we focus our analysis on the patient decision to bypass village clinics. We define a dichotomous outcome variable as 1 if the individual visited local village clinics (VC users) and 0 if the individual visited township health centers, county hospitals, or hospitals outside of the counties for the last sickness of the last year (bypassers). We exclude neighboring village clinics because they only cater to a very small proportion of rural patients (Table A5), and the supply-side data on neighboring village clinics are not available. We also examined patients choosing other facilities. Such facilities, mostly private and immigrant facilities, were not typical healthcare facilities within the healthcare system and supplied very few patients; therefore, we excluded them as well.

To understand how rural residents make decisions between local village clinics and higher levels of health facilities outside of the village, we consider a wide range of determinants on individuals, households, communities, and village providers guided by the Andersen/Aday Health Behavior Model (Aday & Andersen, 1974). According to this model, health care utilization is determined by health need factors, predisposing factors, enabling factors, and health care delivery systems. Table A3 in the Appendix gives a detailed description of the variables considered in this analysis categorized by the Andersen/Aday model.

Health need factors are the most immediate cause of health service use, and the need for health care can be evaluated by doctors or perceived by patients themselves (Aday & Andersen, 1974). Here, we include two categorical variables – the disease type of the last illness diagnosed by doctors and the self-reported health status of last year. The disease type consists of nine categories: acute respiratory infection, non-communication diseases, infectious diseases, digestive system diseases, muscular-skeletal diseases, cerebral diseases, cancer, injuries, and other diseases. Among them, non-communicable diseases refer to heart diseases, hypertension, diabetes, hyperlipemia, and chronic respiratory diseases; infectious diseases include tuberculosis (TB), hepatitis, pertussis, meningitis, and diphtheria. We then categorize all other diseases – including skin diseases, gynecopathy, appendicitis, epilepsy, mental diseases, dental disease, eye disease, anemia, hyperthyroidism, vertigo, and allergies – as “other diseases.” Self-reported health status comprises five categories: excellent, good, ordinary, bad, and poor.

Predisposing factors refer to those variables that describe the individual's characteristics, and these properties normally exist before the onset of illness (Aday & Andersen, 1974). Here, we consider three variables: a continuous age variable, a dummy variable for gender (male), and a categorical variable for the highest level of education with six categories: not educated, primary school, middle school, high school, junior college or technical school, and college or above.

Enabling variables describe the resources available to individuals for health services at the individual, family, and community levels (Aday & Andersen, 1974). Therefore, we consider three variables – a dummy variable for participating in the New Cooperative Medical Scheme (NCMS), family wealth index, and per-capita income of the living village. NCMS is a subsidized insurance scheme covering over 95% of rural residents in China.[5] For those who did not participate in NCMS, they may either have no insurance or participate in other insurance plans, including Urban Employee-Based Medical Insurance, Urban Resident-Based Medical Insurance, and other commercial insurance plans.[6] We construct a family wealth index using a pooled principal component analysis based on the household asset indicators, including television, car, motorcycles, washing machine, computer, fridge, water heater, and LPG stove. The index was then rescaled to vary between a minimum score of 0 and a maximum score of 10. We convert the per-capita income of the living village in 2015 and 2018 to 2011 values using the Consumer Price Index.

Delivery system factors include two elements – resources and organization (Aday & Andersen, 1974). To proxy delivery resources available to the village, we use the village clinic equipment index, number of drugs, number of village doctors per 1000 population, whether the village has licensed (assistant) doctors, and medical practicing years of village doctors. Delivery organization is represented using distance to the nearest township health center and county hospital to reflect access to higher-level facilities. Though "organization" also concerns how

[5] The NCMS reimburses part of health service costs and the co-payment rate varies between provinces and counties and between out-patient and in-patient care (Zhou et al., 2014).
[6] In 2011, the individuals were only asked if they participated in NCMS insurance. Whether or not they had other insurance plans if not participating in NCMS was not surveyed.

patients were treated following the entry into the system, these data are unavailable. We construct a village clinic equipment index using a pooled principal component analysis based on the village clinic equipment indicators, including high-temperature disinfection instrument, ultraviolet disinfection lamp, wound kit, diagnosis bed, sputum aspirator, treatment plate, contaminant tub, tongue depressor, tourniquet, cool bag, oxygen kit, and height-weight scale. Though more equipment indicators were available in the later waves, we use indicators commonly surveyed in three waves to ensure the constructed indexes are comparable across three waves. The index was then rescaled to vary between a minimum score of 0 and a maximum score of 10. We use the maximum number of the equipment index and drug variety available to this village if more than one village clinic operates in the village. The number of village doctors per 1000 population is calculated using village doctors divided by the village population. We average village doctors' medical practicing years if more than one village doctor works in this village.

3.4. Determination of the analysis sample

The detailed sample exclusion rules and determination of the analysis sample are in Appendix Figure A4. Since our primary interest is in estimating the demand change for health services of rural residents living in the sampled areas, we excluded 5320 individuals who reported residing outside the county or migrating out for work during the preceding year in three waves. We then excluded 4519 child observations to focus our analysis on healthcare seeking among adults. Previous studies have shown children have different healthcare demand patterns (Qian *et al.*, 2010). We also excluded 1105 observations from the villages in years when the village had no operating village clinics[7] (5 villages in 2011, 11 villages in 2015, and 5 villages in 2018).

Appendix Table A5 presents the health-seeking behavior of the remaining adult residents across three waves. About 63% to 67% reported being ill in the preceding year. Of these, 68% visited doctors in 2011, and this number decreased to 58% in 2018. As our main research question rests on estimating how rural patients choose between different healthcare facility tiers within the health system over time, we only keep those observations reported being sick and deciding to visit doctors. Two facility choices – neighboring village clinics and others – were excluded due to the reasons stated above. Lastly, we excluded 2% observations missing at determinants, and our final analysis sample contains 5666 observations, consisting of 2124, 1708, and 1834 individuals in 2011, 2015, and 2018.

4. ESTIMATION STRATEGY

Our analysis decomposes the rural patients' demand change for health services into individual contributions of structural changes in measurable determinants. We use a non-linear decomposition technique proposed by Fairlie (1999, 2005), which extends the linear Kitagawa-Oaxaca-Blinder decomposition (Blinder, 1973; Kitagawa, 1955; Oaxaca, 1973) to non-linear models.

The first step in this process is to estimate the probability of seeking care in local village clinics using a binomial logit model, expressed as:

[7] Some villages reported having village clinics and surveyed basic infrastructure and drug inventory of the clinic; however, the affiliated village doctors only took public health duty without providing curative services. We treat such village clinics as non-operating clinics as well.

$$P_i = \Pr(y_i = 1) = F(X_i\hat{\beta}) = \frac{\exp(X_i\hat{\beta})}{1 + \exp(X_i\hat{\beta})} \qquad (1)$$

where F represents the cumulative distribution function from the logistic distribution. y_i is an indicator that equals to 1 if the patient chose the local village clinics and 0 if the patient bypassed the local clinics and visited township health centers, county hospitals, or hospitals outside of the counties (1 if VC user and 0 if bypasser), X is a vector of explanatory variables on health need factors, predisposing factors, enabling factors, and health care delivery system (described above), and $\hat{\beta}$ is a vector of coefficient estimates. The model was estimated using maximum likelihood with standard errors clustered at the village level.

Using the estimates from the binomial logit model, we decompose the mean difference in the probability of utilizing the local village clinics between the two waves as follows:

$$\bar{P}^{T_2} - \bar{P}^{T_1} = \left[\sum_{i=1}^{N^{T_2}} \frac{F(X_i^{T_2}\hat{\beta}^{T_2})}{N^{T_2}} - \sum_{i=1}^{N^{T_1}} \frac{F(X_i^{T_1}\hat{\beta}^{T_2})}{N^{T_1}}\right] + \left[\sum_{i=1}^{N^{T_1}} \frac{F(X_i^{T_1}\hat{\beta}^{T_2})}{N^{T_1}} - \sum_{i=1}^{N^{T_1}} \frac{F(X_i^{T_1}\hat{\beta}^{T_1})}{N^{T_1}}\right] \quad (2)$$

where N stands for the sample sizes for wave T. $\bar{P}$ is the average probability of utilizing the local village clinics in each wave.

In equation (2), the first bracketed term represents the proportion of the demand change explained by the compositional changes in X for two waves of samples. The second term indicates the portion of the demand change that stems from differences in the coefficients on X as well as unobserved determinants. Following previous literature, we do not focus on the second term because the unexplained part in most applications is arbitrary and uninterpretable (Jones, 1983). We apply the techniques suggested in Oaxaca and Ransom (1994) to weigh the first term using the coefficients from the pooled sample of the two waves[8]. This first term estimates the contribution of the entire set of explanatory variables' contribution to the change in utilizing local village clinics between the two waves.

Beyond the aggregate effect, we are also interested in identifying the individual contribution of each explanatory variable to demand change. To estimate the individual contribution of each explanatory variable, Fairlie (1999, 2005) proposes a one-to-one matching approach using the logit coefficients from the pooled sample $\hat{\beta}^*$ as follows:

$$\frac{1}{N^{T_2}}\sum_{i=1}^{N^{T_2}} F(\hat{\beta}_0^* + X_1^{T_2}\hat{\beta}_1^* + X_2^{T_2}\hat{\beta}_2^*, \ldots, + X_k^{T_2}\hat{\beta}_k^*) - F(\hat{\beta}_0^* + X_1^{T_1}\hat{\beta}_1^* + X_2^{T_2}\hat{\beta}_k^*, \ldots, + X_k^{T_2}\hat{\beta}_k^*) \quad (3)$$

The individual contribution of $X_1$to the demand change is then equal to the change in the mean predicted probability of seeking care at local village clinics from replacing the distribution X_1 in T_2 with the distribution X_1 in T_1 while holding constant the distributions of the other variables.

This technique requires equally sized samples of two waves for one-to-one matching. Following Fairlie (1999, 2005), we draw a random subsample of individuals from the wave with the bigger sample and match each individual to the smaller sample based on the probability of utilizing the local village clinics. Since results vary based on the randomly chosen subsample

[8] The first term of the decomposition expression could be weighted using coefficient estimates from the starting wave, the ending wave, or a pooled sample of two waves. Neumark (Neumark, 1988) advocated using the coefficients from a pooled regression over two groups based on theoretical derivation. Oaxaca and Ransom (1994) proved that weighting the terms in the decomposition equation by the coefficients from a pooled sample of two groups yielded the smallest estimated standard errors. This study applies this approach. Table A8 reports the decomposition results using the starting wave coefficients and finds similar results as the main analysis.

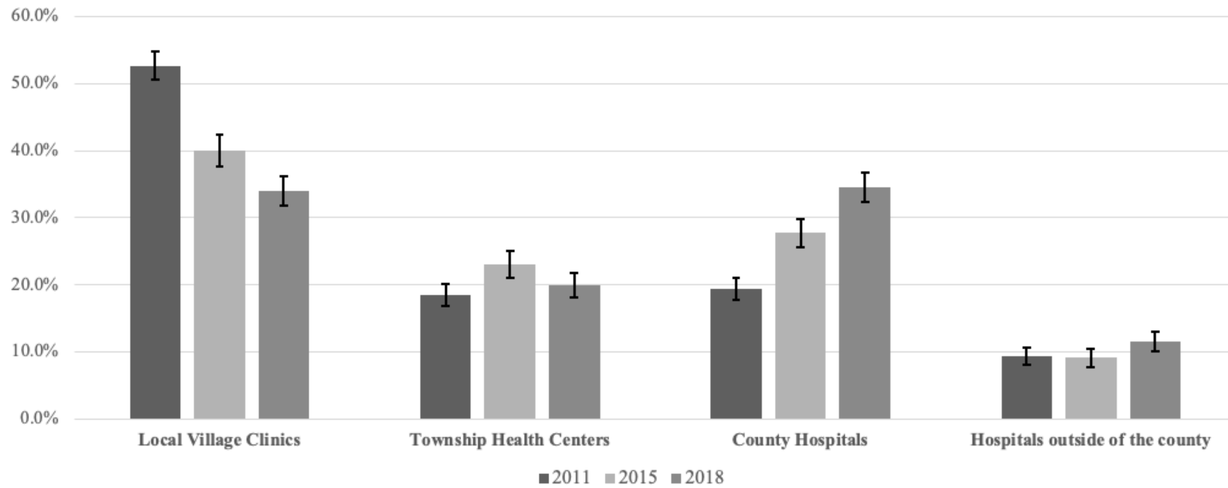
characteristics used in the matching, we report the average estimates of 2000 random subsamples to approximate the decomposition estimates. Results may also be sensitive to the ordering of variables, so we randomize the ordering of variables across the same 2000 replications of the decomposition. Each explanatory variable's individual contribution is calculated from averaging all possible ordering of variables with this large number of replications.

We also present the results from the conventional Kitagawa-Oaxaca-Blinder decomposition in the Appendix. The Kitagawa-Oaxaca-Blinder decomposition is based on a linear regression framework and requires coefficient estimates from the linear probability model and sample means of the explanatory variables. This linear decomposition yields qualitatively similar results to the non-linear decomposition in terms of the contribution estimates (Table A7). However, we center our analysis on the Fairlie non-linear decomposition because it considers the nonlinear nature of our dependent variable using the coefficient estimates from a binomial logit model for decomposition. To further check the robustness of the main decomposition results, we also estimate the decomposition using the coefficients from the starting wave as the weights in the decomposition equation (Table A8) and constraining the sample to households followed in all three waves (Table A9). We find similar results as the main decomposition analysis as well.

5. RESULTS

5.1. Trend in health care utilization

Figure 1 shows that, among those who reported being sick and consulting a doctor during the preceding year, local village clinic utilization dropped significantly, from 52.7% to 34.0% between 2011 and 2018. The 18.7-percentage-point reduction is largely compensated by an increase in utilizing county hospitals. The patient choice of seeking care at county hospitals has increased from 19.4% in 2011 to 34.6% in 2018. Township health centers and other hospitals outside of the county have also observed a slight (though insignificant) increase in their utilization share.



Note: Error bars give 95% CIs for the proportions

Figure 1. Changes in Facility Choice of Rural Patients in China, 2011-2018

5.2. Trend in determinants

Table 2 shows that considerable changes in the distribution of a few core determinants occurred in rural China between 2011 and 2018. First, the average age of patients in our sample increased by 5.5 years from 52.1 in 2011 to 57.6 in 2018. The proportion aged 50 and above grew from 57.8% to 74.3% during this period. Though patients are self-selected into utilizing health services, and we are cautious about concluding that we observed a population aging from our sample, this trend is consistent with the demographic change in recent years. The latest 2010 population census has demonstrated that China's population is aging rapidly, with millions of young rural migrants living and working in urban areas (Peng, 2011). The composition of the population remaining in rural areas, therefore, is increasingly elderly. This population aging naturally implies an increasing demand for health services. Consistent with this, patients in 2018 had a significantly increased share of non-communicable diseases, cerebral diseases, musculoskeletal diseases. Among these, the share of non-communicable disease increased by the largest amount from 15% to 22%. To explore the relationship between population aging and disease trends in more detail, Table A6 in the Appendix divides the sample into two age groups using the cutoff at age 50. We find both groups observed an increase in their share of non-communicable disease and musculoskeletal diseases, with the age group older than 50 having a larger increase than the younger group. The older age group also had an increased share of cerebral diseases and cancer, whereas the younger age group did not find this trend. Overall, patients in 2018 reported worse health than in 2011.

In terms of “predisposing” and “enabling” factors, we observed a significant increase in rural residents’ economic status. Although the education level was largely unchanged with less than 5% with education higher than high school, the household wealth index and the per capita income in 2018 were significantly higher than in 2011. Gender composition and NCMS participation rate remained mostly unchanged during the period.

We also observed several significant changes to the health system over the same period in the sample villages. Medical resources, both the number of drugs and the number of village doctors per 1000 population, have dropped significantly between 2011 and 2018. However, there was a slightly increased share of patients living in a village with nationally-licensed (assistant) doctors in 2018 (33% to 39%), though not statistically significant. Most rural residents were still served by village doctors with low medical certification and long medical practice years. The village clinic equipment index and the distance to the nearest township health center and county hospital were mostly unchanged during this period.

Table 2. Summary Statistics by Year

	2011	2015	2018	P-value
	(1)	(2)	(3)	
Number of observations	**2124**	**1708**	**1834**	
Village clinic user (0/1)	1119 (53%)	683 (40%)	624 (34%)	<0.001
Health Need Variables				
Disease type				
Acute Respiratory Infection (0/1)	1117 (53%)	758 (44%)	710 (39%)	<0.001
Non-communicable Disease (0/1)	308 (15%)	379 (22%)	401 (22%)	<0.001
Infectious Disease (0/1)	11 (1%)	7 (<1%)	7 (<1%)	0.761
Digestive System Disease (0/1)	148 (7%)	118 (7%)	139 (8%)	0.747
Musculo-skeletal Disease (0/1)	135 (6%)	123 (7%)	165 (9%)	0.002
Cerebral Disease (0/1)	56 (3%)	73 (4%)	95 (5%)	<0.001
Cancer (0/1)	20 (1%)	20 (1%)	40 (2%)	0.018
Injury (0/1)	67 (3%)	49 (3%)	53 (3%)	0.877
Other diseases (0/1)	262 (12%)	181 (11%)	224 (12%)	0.205
Self-reported health status				
Excellent (0/1)	341 (16%)	317 (19%)	256 (14%)	0.016
Good (0/1)	643 (30%)	361 (21%)	499 (27%)	<0.001
Ordinary (0/1)	559 (26%)	516 (30%)	464 (25%)	0.022
Bad (0/1)	494 (23%)	399 (23%)	527 (29%)	0.002
Poor (0/1)	87 (4%)	115 (7%)	88 (5%)	0.028
Predisposing Variables				
Age (years)	52.1 (15.1)	55.7 (14.6)	57.6 (14.2)	<0.001
Male (0/1)	915 (43%)	769 (45%)	794 (43%)	0.234
Education				
Not educated (0/1)	442 (21%)	346 (20%)	361 (20%)	0.599
Primary school (0/1)	749 (35%)	589 (34%)	690 (38%)	0.115
Middle school (0/1)	700 (33%)	557 (33%)	570 (31%)	0.326
High school (0/1)	158 (7%)	140 (8%)	147 (8%)	0.537
Junior college or technical school (0/1)	49 (2%)	56 (3%)	51 (3%)	0.119
College or above (0/1)	26 (1%)	20 (1%)	15 (1%)	0.427
Enabling Variables				
NCMS Insurance (0/1)	2019 (95%)	1633 (96%)	1712 (93%)	0.074
Family wealth index (0-10 scale points)	5.7 (2.2)	6.8 (2.2)	6.5 (2.0)	<0.001
Per capita income in 2011 value, by village (Yuan)	5418.6 (2856.6)	8856.0 (5542.8)	10485.4 (5828.4)	<0.001
Health Care Delivery System				
Village clinic equipment index (0-10 scale points)	8.3 (1.4)	8.2 (1.4)	8.5 (1.3)	0.192
Number of drugs available in village	294.3 (208.6)	225.6 (185.0)	198.7 (155.1)	<0.001
Number of village doctors per 1000 population	2.2 (2.1)	1.3 (0.8)	1.2 (0.7)	<0.001
Having nationally-licensed doctor (0/1)	706 (33%)	648 (38%)	724 (39%)	0.498
Medical practicing years of village doctors (years)	25.0 (10.6)	27.1 (11.0)	29.7 (10.9)	<0.001
Distance to the nearest township health center (km)	5.2 (4.6)	5.4 (5.5)	5.3 (5.5)	0.737
Distance to the nearest county hospital (km)	24.1 (20.3)	25.0 (23.1)	24.3 (23.0)	0.669

Note. Data are n (%) for binary variables and mean (SD) for continuous variables. F-statistic p-values are inferred from regressing the year indicator on each variable with clustered standard errors at the village level. Non-communicable diseases include heart diseases, hypertension, diabetes, hyperlipemia, and chronic respiratory disease; Infectious diseases include TB, hepatitis, pertussis, meningitis, and diphtheria; Other diseases include skin diseases, gynecopathy, appendicitis, epilepsy, mental diseases, dental disease, eye disease, anemia, hyperthyroidism, vertigo, and allergy. People not participating in the New Rural Cooperative Medical Scheme (NCMS) may have no insurance or participate in other insurance plans, including Urban Employee-Based Medical Insurance, Urban Resident-Based Medical Insurance, and other commercial insurance plans.

5.3. Correlates of health care utilization

Table 3 reports the marginal effects of the explanatory variables on the probability of using the local village clinic. While Fairlie non-linear decomposition in this analysis mainly relies on the logit model, we provide logit and linear probability model results with and without county fixed effects, showing a consistent pattern in the association between facility choice and its determinants.

Table 3 shows that patients with diseases other than acute respiratory infections, patients with more negative self-reported health status, and higher educated patients were more likely to bypass the local village clinics. Being elderly increased the probability of using village clinics while holding all else constant. Having NCMS insurance was also associated with a higher probability of using the village clinic, though more than 90% of the sample had NCMS insurance (Table 2). Most variables reflecting medical resources at the village level, such as the number of drugs, number of doctors, and village doctors' medical qualification, were positively associated with the probability of using village clinics. The probability of using village clinics also increased significantly with a longer distance to the nearest township health center, while county hospital distance was insignificant after controlling for other factors. A higher ratio of village doctors to population was associated with an increased probability of using village clinics but became insignificant after controlling county fixed-effects. Other factors, such as gender, economic status, village clinic equipment index, and medical practicing year of village doctors, were not significantly correlated with the probability of visiting local village clinics.

Table 3. Regression Results

Dependent Variables Village Clinic User (Y=1/N=0)	Year Fix-Effect Only		Year Fixed-Effect & County Fixed Effect	
	Logit (1)	OLS (2)	Logit (3)	OLS (4)
Health Need Variables				
Disease type (Base category: Acute Respiratory Infection)				
Non-communicable Disease	-0.364***	-0.374***	-0.363***	-0.373***
	(0.024)	(0.024)	(0.021)	(0.021)
Infectious Disease	-0.441***	-0.439***	-0.428***	-0.429***
	(0.062)	(0.066)	(0.059)	(0.061)
Digestive System Disease	-0.447***	-0.454***	-0.439***	-0.444***
	(0.030)	(0.030)	(0.028)	(0.028)
Musculo-skeletal Disease	-0.478***	-0.486***	-0.466***	-0.473***
	(0.027)	(0.027)	(0.025)	(0.027)
Cerebral Disease	-0.549***	-0.537***	-0.545***	-0.537***
	(0.035)	(0.035)	(0.030)	(0.032)
Cancer	-0.566***	-0.535***	-0.563***	-0.539***
	(0.049)	(0.039)	(0.047)	(0.041)
Injury	-0.553***	-0.549***	-0.547***	-0.541***
	(0.032)	(0.031)	(0.027)	(0.029)
Other diseases	-0.465***	-0.470***	-0.457***	-0.465***
	(0.027)	(0.026)	(0.024)	(0.024)
Self-reported health status (Base: Excellent)				
Good	-0.067***	-0.066***	-0.044**	-0.045**
	(0.022)	(0.022)	(0.020)	(0.020)
Ordinary	-0.087***	-0.083***	-0.055***	-0.052***
	(0.022)	(0.021)	(0.019)	(0.019)
Bad	-0.139***	-0.134***	-0.100***	-0.100***
	(0.024)	(0.023)	(0.022)	(0.021)
Poor	-0.175***	-0.165***	-0.137***	-0.132***
	(0.034)	(0.030)	(0.034)	(0.029)
Predisposing Variables				
Age (years)	0.002***	0.002**	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Male (0/1)	0.009	0.009	0.008	0.008
	(0.010)	(0.010)	(0.010)	(0.010)
Education (Base: not educated)				
Primary school	-0.042**	-0.039**	-0.033**	-0.029*
	(0.016)	(0.016)	(0.015)	(0.016)
Middle school	-0.076***	-0.074***	-0.061***	-0.058***
	(0.022)	(0.022)	(0.020)	(0.021)
High school	-0.061**	-0.059**	-0.051*	-0.048*
	(0.030)	(0.029)	(0.028)	(0.029)
Junior college or technical school	-0.158***	-0.164***	-0.126***	-0.129***
	(0.038)	(0.042)	(0.036)	(0.042)
College and above	-0.286***	-0.342***	-0.269***	-0.314***
	(0.048)	(0.059)	(0.047)	(0.059)
Enabling Variables				
NCMS Insurance (0/1)	0.071**	0.065**	0.077***	0.069**

	(0.032)	(0.030)	(0.028)	(0.027)
Family wealth index (0-10 scale points)	0.006*	0.006*	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)
Per capita income of living village in 2011 value (Yuan, log-transformed)	-0.025	-0.028	0.015	0.019
	(0.022)	(0.022)	(0.020)	(0.021)
Health Care Delivery System				
Village clinic equipment index (0-10 scale points)	0.009	0.011	0.008	0.012
	(0.009)	(0.009)	(0.008)	(0.008)
Number of drugs available in village (log)	0.086***	0.080***	0.086***	0.078***
	(0.017)	(0.015)	(0.017)	(0.015)
Number of village doctors per 1000 population	0.012**	0.014**	0.008	0.009
	(0.006)	(0.006)	(0.006)	(0.006)
Having nationally-licensed doctor (0/1)	0.070***	0.073***	0.050***	0.051**
	(0.025)	(0.026)	(0.019)	(0.020)
Medical practicing years of village doctors (years)	-0.001	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to the nearest township health center (km)	0.009***	0.008***	0.007***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance to the nearest county hospital (km)	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Year 2015	-0.051**	-0.052**	-0.066***	-0.070***
	(0.022)	(0.023)	(0.020)	(0.020)
Year 2018	-0.071***	-0.075***	-0.097***	-0.108***
	(0.027)	(0.027)	(0.024)	(0.024)
Observations	5666	5666	5666	5666

Note. Marginal effects are reported. Standard errors in parentheses account for clustering at the village level.
** p<0.10, ** p<0.05, *** p<0.01*

5.4. Fairlie non-linear decomposition

Table 4 presents the decomposition of the change in the local village clinic utilization. The third column indicates that the 18.7 percentage point decrease in the probability of using local village clinics between 2011 and 2018 is mainly attributable to the compositional changes in the explanatory variables (57.8%) while unobserved factors and differential effects of the explanatory variables account for the remaining 42.2%.

The detailed decomposition reveals that the change in disease composition is the largest contributor to the reduced use of village clinics (33.2%), followed by decreased drug availability (19.8%). Two other determinants, increasing village doctor practicing years and the deteriorated population health status, also significantly contribute to the reduction in utilizing village clinics (4.3% and 3.2%), though not in large magnitude. Despite the considerable increase in wealth of rural residents and decrease in the number of doctors, their contributions to the reduced utilization of village clinics are minimal, implying that they are not the primary reasons for the reduction after controlling for other determinants. On the other hand, the aging of patients and the slightly increased share of nationally-licensed (assistant) doctors are significantly associated with greater patient retention at village clinics (-7.5% and -1.6%).

Table 4 also shows the decomposition results comparing 2011 to 2015 and 2015 to 2018. The utilization of village clinics has dropped by 12.7 percentage points between 2011 and 2015, and 6 percentage points between 2015 and 2018. The decomposition results comparing 2011 to 2015 are consistent with those comparing 2011 to 2018, whereas the results comparing 2015 to 2018 are slightly different. Consistent with the results from 2011 to 2018, the changes in disease composition and the decreased drug availability have the largest contributions to the reduction in both periods. The disease composition changes explain 25.2% of the decrease over 2011 to 2015 and 40.0% of the decline over 2015 to 2018. The decreased drug availability accounts for 19.7% of the reduction over 2011 to 2015 and 16.7% of the decrease over 2015 to 2018.

Except for these two determinants, other determinants have differing contributions in the two periods. The decreased doctor availability is a significant contributor (9.4%) to the 12.7 percentage-point reductions over 2011 to 2015, and the aging of patients and the increased share of doctors with high qualification have significant contributions to retaining patients at the village level (-4.7% and -3.1%) over the same period. Similar results do not show up from the decomposition comparing 2015 to 2018. In contrast, the increased village wealth is a significant determinant of retaining patients at the village (-15.0%) from 2015 to 2018, while its contribution is not significant over 2011 to 2015.

Table 4. The Fairlie Non-linear Decomposition

	2011 to 2018 (N=3958)			2011 to 2015 (N=3832)			2015 to 2018 (N=3542)		
	Estimates (1)	SE (2)	Explained Change (3)	Estimates (4)	SE (5)	Explained Change (6)	Estimates (7)	SE (8)	Explained Change (9)
Initial Proportion of VC Utilization	0.527	--	--	0.527	--	--	0.400	--	--
End Proportion of VC Utilization	0.340	--	--	0.400	--	--	0.340	--	--
Total Change	**-0.187**	--	--	**-0.127**	--	--	**-0.060**	--	--
Contribution of Explanatory Variables to Change									
Disease composition	-0.062***	(0.003)	33.2%	-0.032***	(0.002)	25.2%	-0.024***	(0.002)	40.0%
Health status	-0.006***	(0.001)	3.2%	-0.003*	(0.002)	2.4%	-0.002	(0.002)	3.3%
Demographics	0.014***	(0.003)	-7.5%	0.006***	(0.002)	-4.7%	0.001	(0.001)	-1.7%
Education	0.001	(0.001)	-0.5%	-0.001	(0.001)	0.8%	0.001**	(0.001)	-1.7%
Insurance	-0.001**	(0.000)	0.5%	0.001**	(0.000)	-0.8%	-0.001	(0.001)	1.7%
Household wealth	-0.003	(0.003)	1.6%	-0.001	(0.004)	0.8%	0.001	(0.001)	-1.7%
Village economic level	-0.007	(0.010)	3.7%	0.010	(0.007)	-7.9%	0.009***	(0.003)	-15.0%
Medical equipment availability	0.001	(0.001)	-0.5%	-0.001*	(0.001)	0.8%	0.001	(0.001)	-1.7%
Drug availability	-0.037***	(0.005)	19.8%	-0.025***	(0.004)	19.7%	-0.010***	(0.002)	16.7%
Doctor availability	-0.005	(0.005)	2.7%	-0.012**	(0.005)	9.4%	0.000	(0.000)	0.0%
Doctor qualification	0.003***	(0.001)	-1.6%	0.004***	(0.001)	-3.1%	0.000	(0.000)	0.0%
Doctor medical practicing year	-0.008**	(0.003)	4.3%	-0.003	(0.002)	2.4%	-0.003	(0.002)	5.0%
Distance to higher-tiered health facilities	-0.000	(0.000)	0.0%	0.001**	(0.000)	-0.8%	-0.000	(0.000)	0.0%
County fixed-effect	0.003	(0.003)	-1.6%	0.006*	(0.003)	-4.7%	0.007**	(0.003)	-11.7%
Explained Change by All Included Variables	**-0.108**	--	**57.8%**	**-0.050**	--	**39.4%**	**-0.019**	--	**31.7%**
Unexplained Change	**-0.079**	--	**42.2%**	**-0.077**	--	**60.6%**	**-0.041**	--	**68.3%**

Note. The coefficients from a pooled sample of two waves are used in the decomposition estimation. Fairlie non-linear decomposition randomly orders the variables across decomposition replications to address path dependence. A total of 2000 decomposition replications are performed to approximate the decomposition estimates. The estimation model is the logit model.
** p<0.10, ** p<0.05, *** p<0.01*

6. DISCUSSION AND CONCLUSION

In this paper, we study the change in the demand for healthcare in rural areas of China using longitudinal and nationally-representative data from 2011 to 2018. Overall, we find an 18.7-percentage-point decrease in the probability of utilizing the local village clinics in rural China from 2011 to 2018. The increased use of county hospitals largely compensated for this reduction in village clinic utilization.

Our decomposition analysis suggests that the structural changes in a few key determinants explained more than half of the reduction in village clinic utilization. The single factor contributing the most to the decrease in village clinic utilization, accounting for 33.2% of the reduction, appears to be the changing composition of the diseases, with a large increase in non-communicable diseases serving as a major driver pushing patients towards the higher-tiered facilities. The reasons why patients with non-communicable diseases tend to bypass could be due to supply-side and demand-side factors. First, though village doctors are obliged to manage non-communicable conditions in their catchment areas, they may have little capacity or incentives to treat such diseases. Li *et al.* (2017) reported that some village clinics were incentivized to provide basic public health services rather than clinical care by subsidies from the public health service program. Guo *et al.* (2020) documented the limited capacity of village doctors to diagnose and manage heart diseases. Second, patients may have strong preferences for receiving care at high-tiered hospitals when they perceive the quality of care delivered in these facilities to be higher. The NCMS insurance scheme may amplify such intentions when patients perceive their illness as severe and require hospitalization. While the co-payment rates of NCMS insurance vary between provinces and counties, they usually have generous reimbursement for inpatient care with the incentive to protect against catastrophic health costs. Outpatient care has a low ceiling of coverage (CNY ¥200/USD $30 in some counties), and NCMS does not cover all village clinics (Zhou, Li, & Hesketh, 2014).

Decreased drug availability at the village level is another major reason for the decrease in village clinic utilization, accounting for 19.8% of the reduction. The reasons for decreasing drug availability at the village level are unclear. One explanation could be the decreasing emphasis of village doctors on providing curative care while delivering public health services. Another potential cause may be efforts to increase regulation of drug sales. The introduction of essential drug list and zero markup drug policy for the primary level, as part of the national reforms, restricted the number of drugs that primary providers can prescribe to reduce provider incentives to overprescribe unnecessary drugs (Chen, 2009). This regulation may also be the reason why township health centers did not absorb the increased bypassers. Zhou *et al.* (2014) investigated the impacts of health reforms on township health workers and reported that the essential drug list was insufficient for the range of conditions managed in township health centers. When appropriate drugs were not on the list, township doctors tended to refer patients to county hospitals.

Our results are subject to two important limitations. First, the estimates presented should not be interpreted as causal relationships. While not causal, we believe results to be informative of the relative importance of changes in determinants in shaping changes in demand for healthcare in rural China during a period of dramatic reforms, the design of which complicate the causal analysis of impacts. Second, this analysis only focuses on how patients selected health facilities within the health system after deciding to consult a doctor, though patients could have visited pharmacies for self-treatment. The decreased availability of health services at village clinics could have forced patients to consider self-medication if the symptoms were not severe.

We conclude that the structural changes in patient disease patterns and the decreased medical resources at the primary level are responsible for the substantial drop in primary care utilization. Gatekeeping has been proposed as a potential means to address the inefficient use of higher-tiered level facilities in China in recent years. Our findings highlight that the infrastructure and workforce at lower-level facilities in rural areas remain insufficient to meet patient demand. The fact that rates of bypassing of village and township providers continue to increase may indicate that patients perceive the quality of care delivered in these facilities to be low relative to their increasing demands for higher quality healthcare. Meanwhile, other policy interventions implemented during the same period may also have contributed to persistent bypassing.

REFERENCES

Aday, L. A., & Andersen, R. (1974). A framework for the study of access to medical care. *Health Services Research*, *9*(3), 208–220. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1071804/pdf/hsresearch00560-0030.pdf

Akin, J. S., & Hutchinson, P. (1999). Health-care facility choice and the phenomenon of bypassing. *Health Policy and Planning*, *14*(2), 135–151. https://doi.org/10.1093/heapol/14.2.135

Anand, S., Fan, V. Y., Zhang, J., Zhang, L., Ke, Y., Dong, Z., & Chen, L. C. (2008). China's human resources for health: quantity, quality, and distribution. *The Lancet*, *372*(9651), 1774–1781. https://doi.org/10.1016/S0140-6736(08)61363-X

Babiarz, K. S., Miller, G., Yi, H., Zhang, L., & Rozelle, S. (2010). New evidence on the impact of China's New Rural Cooperative Medical Scheme and its implications for rural primary healthcare: multivariate difference-in-difference analysis. *BMJ*, *341*(oct21 2), c5617–c5617. https://doi.org/10.1136/bmj.c5617

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, *8*(4), 436. https://doi.org/10.2307/144855

Brown, P. H., & Theoharides, C. (2009). Health-seeking behavior and hospital choice in China's New Cooperative Medical System. *Health Economics*, *18*(S2), S47–S64. https://doi.org/10.1002/hec.1508

Cai, R., Tang, J., Deng, C., Lv, G., Xu, X., Sylvia, S., & Pan, J. (2019). Violence against health care workers in China, 2013–2016: evidence from the national judgment documents. *Human Resources for Health*, *17*(1), 103. https://doi.org/10.1186/s12960-019-0440-y

Chao, J., Lu, B., Zhang, H., Zhu, L., Jin, H., & Liu, P. (2017). Healthcare system responsiveness in Jiangsu Province, China. *BMC Health Services Research*, *17*(1), 31. https://doi.org/10.1186/s12913-017-1980-2

Chen, Z. (2009). Launch of the health-care reform plan in China. *The Lancet*, *373*, 1322–1324. https://doi.org/10.1016/S0140-6736(09)60753-4

Ding, Y., Smith, H. J., Fei, Y., Xu, B., Nie, S., Yan, W., … Dong, H. (2013). Factors influencing the provision of public health services by village doctors in Hubei and Jiangxi provinces, China. *Bulletin of the World Health Organization*, *91*(1), 64–69. https://doi.org/10.2471/BLT.12.109447

Eggleston, K., Ling, L., Qingyue, M., Lindelow, M., & Wagstaff, A. (2008). Health service delivery in China: a literature review. *Health Economics*, *17*(2), 149–165. https://doi.org/10.1002/hec.1306

Fairlie, R. W. (1999). The Absence of the African-American Owned Business: An Analysis of the Dynamics of Self-Employment. *Journal of Labor Economics*, *17*(1), 80–108. https://doi.org/10.1086/209914

Fairlie, R. W. (2005). An extension of the Blinder-Oaxaca decomposition technique to logit and probit models. *Journal of Economic and Social Measurement*, *30*(4), 305–316. https://doi.org/10.3233/JEM-2005-0259

Fu, P., Wang, Y., Liu, S., Li, J., Gao, Q., Zhou, C., … Sylvia, S. (2020). Analysing the preferences for family doctor contract services in rural China: a study using a discrete choice experiment. *BMC Family Practice*, *21*(1), 148. https://doi.org/10.1186/s12875-020-01223-9

Gauthier, B., & Wane, W. (2011). Bypassing health providers: the quest for better price and quality of health care in Chad. *Social Science & Medicine*, *73*(4), 540–549.

https://doi.org/10.1016/j.socscimed.2011.06.008

Guo, W., Sylvia, S., Umble, K., Chen, Y., Zhang, X., & Yi, H. (2020). The competence of village clinicians in the diagnosis and treatment of heart disease in rural China: A nationally representative assessment. *The Lancet Regional Health - Western Pacific*, *2*, 100026. https://doi.org/10.1016/j.lanwpc.2020.100026

Hesketh, T., Wu, D., Mao, L., & Ma, N. (2012). Violence against doctors in China. *BMJ*, *345*(sep07 1), e5730–e5730. https://doi.org/10.1136/bmj.e5730

Hsiao, W. C. L. (1995). The Chinese health care system: Lessons for other nations. *Social Science & Medicine*, *41*(8), 1047–1055. https://doi.org/10.1016/0277-9536(94)00421-O

Hu, X., Cook, S., & Salazar, M. A. (2008). Internal migration and health in China. *The Lancet*, *372*(9651), 1717–1719. https://doi.org/10.1016/S0140-6736(08)61360-4

Jones, F. L. (1983). On Decomposing the Wage Gap: A Critical Comment on Blinder's Method. *The Journal of Human Resources*, *18*(1), 126. https://doi.org/10.2307/145660

Kitagawa, E. M. (1955). Components of a Difference Between Two Rates*. *Journal of the American Statistical Association*, *50*(272), 1168–1194. https://doi.org/10.1080/01621459.1955.10501299

Leonard, K. L., Mliga, G. R., & Haile Mariam, D. (2002). Bypassing Health Centres in Tanzania: Revealed Preferences for Quality. *Journal of African Economies*, *11*(4), 441–471. https://doi.org/10.1093/jae/11.4.441

Li, X., Krumholz, H. M., Yip, W., Cheng, K. K., De Maeseneer, J., Meng, Q., … Hu, S. (2020). Quality of primary health care in China: challenges and recommendations. *The Lancet*, *395*(10239), 1802–1812. https://doi.org/10.1016/S0140-6736(20)30122-7

Li, X., Lu, J., Hu, S., Cheng, K., De Maeseneer, J., Meng, Q., … Hu, S. (2017). The primary health-care system in China. *The Lancet*, *390*(10112), 2584–2594. https://doi.org/10.1016/S0140-6736(17)33109-4

Liu, Y., Kong, Q., Yuan, S., & van de Klundert, J. (2018). Factors influencing choice of health system access level in China: A systematic review. *PloS One*, *13*(8), e0201887. https://doi.org/10.1371/journal.pone.0201887

Neumark, D. (1988). Employers' Discriminatory Behavior and the Estimation of Wage Discrimination. *The Journal of Human Resources*, *23*(3), 279. https://doi.org/10.2307/145830

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, *14*(3), 693. https://doi.org/10.2307/2525981

Oaxaca, R. L., & Ransom, M. R. (1994). On discrimination and the decomposition of wage differentials. *Journal of Econometrics*, *61*(1), 5–21. https://doi.org/10.1016/0304-4076(94)90074-4

Peng, X. (2011). China's Demographic History and Future Challenges. *Science*, *333*(6042), 581–587. https://doi.org/10.1126/science.1209396

Powell-Jackson, T., Yip, W. C.-M., & Han, W. (2015). Realigning Demand and Supply Side Incentives to Improve Primary Health Care Seeking in Rural China. *Health Economics*, *24*(6), 755–772. https://doi.org/10.1002/hec.3060

Qian, D., Lucas, H., Chen, J., Xu, L., & Zhang, Y. (2010). Determinants of the use of different types of health care provider in urban China: a tracer illness study of URTI. *Health Policy*, *98*(2–3), 227–235. https://doi.org/10.1016/j.healthpol.2010.06.014

Qian, D., Pong, R. W., Yin, A., Nagarajan, K. V, & Meng, Q. (2009). Determinants of health care demand in poor, rural China: the case of Gansu Province. *Health Policy and Planning*, *24*(5), 324–334. https://doi.org/10.1093/heapol/czp016

Sylvia, S., Shi, Y., Xue, H., Tian, X., Wang, H., Liu, Q., … Rozelle, S. (2015). Survey using incognito standardized patients shows poor quality care in China's rural clinics. *Health Policy and Planning*, *30*(3), 322–333. https://doi.org/10.1093/heapol/czu014

Sylvia, S., Xue, H., Zhou, C., Shi, Y., Yi, H., Zhou, H., … Das, J. (2017). Tuberculosis detection and the challenges of integrated care in rural China: A cross-sectional standardized patient study. *PLoS Medicine*, *14*(10), e1002405. https://doi.org/10.1371/journal.pmed.1002405

Yang, G., Kong, L., Zhao, W., Wan, X., Zhai, Y., Chen, L. C., & Koplan, J. P. (2008). Emergence of chronic non-communicable diseases in China. *The Lancet*, *372*(9650), 1697–1705. https://doi.org/10.1016/S0140-6736(08)61366-5

Yang, H., Huang, X., Zhou, Z., Wang, H. H. X., Tong, X., Wang, Z., … Lu, Z. (2014). Determinants of Initial Utilization of Community Healthcare Services among Patients with Major Non-Communicable Chronic Diseases in South China. *PLoS ONE*, *9*(12), e116051. https://doi.org/10.1371/journal.pone.0116051

Yip, W. C.-M., Hsiao, W. C., Chen, W., Hu, S., Ma, J., & Maynard, A. (2012). Early appraisal of China's huge and complex health-care reforms. *The Lancet*, *379*(9818), 833–842. https://doi.org/10.1016/S0140-6736(11)61880-1

Yip, W. C.-M., Hsiao, W., Meng, Q., Chen, W., & Sun, X. (2010). Realignment of incentives for health-care providers in China. *The Lancet*, *375*(9720), 1120–1130. https://doi.org/10.1016/S0140-6736(10)60063-3

Yip, W. C., Wang, H., & Liu, Y. (1998). Determinants of patient choice of medical provider: a case study in rural China. *Health Policy and Planning*, *13*(3), 311–322. https://doi.org/10.1093/heapol/13.3.311

Yip, W., Fu, H., Chen, A. T., Zhai, T., Jian, W., Xu, R., … Chen, W. (2019). 10 years of health-care reform in China: progress and gaps in Universal Health Coverage. *The Lancet*, *394*(10204), 1192–1204. https://doi.org/10.1016/S0140-6736(19)32136-1

Yu, B., Meng, Q., Collins, C., Tolhurst, R., Tang, S., Yan, F., … Liu, X. (2010). How does the New Cooperative Medical Scheme influence health service utilization? A study in two provinces in rural China. *BMC Health Services Research*, *10*(1), 116. https://doi.org/10.1186/1472-6963-10-116

Zhang, L., Wang, Z., Qian, D., & Ni, J. (2014). Effects of changes in health insurance reimbursement level on outpatient service utilization of rural diabetics: evidence from Jiangsu Province, China. *BMC Health Services Research*, *14*(1), 185. https://doi.org/10.1186/1472-6963-14-185

Zhou, X. D., Li, L., & Hesketh, T. (2014). Health system reform in rural China: Voices of healthworkers and service-users. *Social Science & Medicine*, *117*, 134–141. https://doi.org/10.1016/j.socscimed.2014.07.040

APPENDIX

Table A1. Sample Summary: Villages, Village Clinics, and Village Clinicians

Variables	2011	2015	2018
	(1)	(2)	(3)
Number of Villages Surveyed	**100**	**100**	**100**
Village population	1438.1 (861.7)	1758.8 (1302.2)	1868.1 (1314.3)
Per capita income of the living village, in 2011 value (Yuan)	5513.5 (3040.0)	8289.6 (5326.0)	10437.7 (5961.7)
Villages with no village clinics	5 (5%)	8 (8%)	4 (4%)
Village having 1 village clinic	58 (58%)	70 (70%)	75 (75%)
Village having 2 village clinics	27 (27%)	18 (18%)	14 (14%)
Village having more than 2 village clinics	10 (10%)	4 (4%)	7 (7%)
Number of Village Clinics Surveyed	**143**	**122**	**124**
Medical equipment index (PCA Score, 0-10 scale points)	7.6 (1.9)	7.7 (2.0)	8.0 (1.8)
Number of drugs in inventory	246.1 (187.8)	200.8 (180.0)	170.7 (145.5)
Number of Village Clinicians Surveyed	**208**	**161**	**152**
Age of the village doctor	48.2 (12.2)	49.8 (11.2)	51.9 (10.9)
Medical practicing years	25.4 (12.8)	28.3 (12.8)	30.3 (12.4)
Male doctor	153 (74%)	119 (74%)	116 (76%)
Education level			
Primary school	4 (2%)	3 (2%)	2 (1%)
Middle school	51 (25%)	22 (14%)	21 (14%)
High school	24 (12%)	16 (10%)	11 (7%)
Technical school	101 (49%)	90 (56%)	87 (57%)
Junior college	27 (13%)	28 (17%)	26 (17%)
College	1 (<1%)	2 (1%)	5 (3%)
Certification			
Licensed doctor	16 (8%)	15 (9%)	17 (11%)
Licensed assistant doctor	31 (15%)	19 (12%)	17 (11%)
Certified village doctor	149 (72%)	116 (72%)	118 (78%)
Other certifications	3 (1%)	1 (1%)	0 (0%)
No certifications	9 (4%)	10 (6%)	0 (0%)

Note: Data are n (%) for binary variables and mean (SD) for continuous variables. Clinicians with other certifications could be certified nurses and pharmacists. The village doctor certificate is not a regular license. Village doctors with village doctor certificates are allowed to practice only in local villages. Village clinic equipment index is constructed using the first principal component of echo meter, sphygmomanometer, thermometer, high-temperature disinfection, medical kit, wound kit, diagnosis bed, sputum aspirator, treatment plate, contaminant tub, tongue depressor, tourniquet, cool bag, oxygen kit, and height-weight scale. The index is rescaled to 0-10 scale points.

Table A2. Comparison between Followed and Newly Added Households

	2011 (N=9347)	2015 (N=8309)		2018 (N=8936)	
	Households	**Followed Households**	**New Households**	**Followed Households**	**New Households**
No. of Surveyed Household Members	9347	7452	857	8038	898
Age (years)	37.4 (20.6)	39.9 (21.5)	40.3 (21.6)	42.3 (22.2)	38.9 (21.1)
Male (0/1)	50%	52%	53%	51%	51%
Education					
Not educated (0/1)	19%	17%	18%	17%	16%
Primary school (0/1)	28%	30%	25%	29%	30%
Middle school (0/1)	36%	34%	35%	34%	35%
High school (0/1)	9%	9%	10%	9%	8%
Junior college/technical school (0/1)	6%	6%	8%	7%	7%
College or above (0/1)	3%	4%	4%	5%	4%
Self-reported health status					
Excellent (0/1)	38%	41%	45%	30%	24%
Good (0/1)	33%	27%	27%	40%	45%
Ordinary (0/1)	17%	19%	15%	16%	17%
Bad (0/1)	10%	10%	10%	12%	12%
Poor (0/1)	2%	2%	3%	2%	2%
Family wealth index (0-10 scale points)	5.8 (2.2)	6.8 (2.2)	6.7 (2.1)	6.7 (2.0)	6.8 (2.1)
Sick during the last year (0/1)	63%	57%	51%	60%	62%

Note. Household size changed with births, marriages, and deaths of the household members over the years. The family wealth index is constructed using a pooled principal component analysis based on household asset indicators. The index is rescaled to 0-10 scale points.

Table A3. Variable Descriptions

Variables	Descriptions
Dependent Variable	
Village clinic user (0/1)	"1" if the individual visited village clinics when seeking health services for the last illness of last year, and "0" if visited township health centers, county hospitals, or hospitals outside the county.
Health Need Variables	
Disease type (category)	Diseases type of the last illness of last year, including nine categories: acute respiratory infection, non-communication disease, infectious disease, digestive system disease, muscular-skeletal disease, cerebral disease, cancer, injury, and other diseases. Among them, non-communicable diseases include heart diseases, hypertension, diabetes, hyperlipemia, and chronic respiratory diseases; Infectious diseases include TB, hepatitis, pertussis, meningitis, and diphtheria; Other diseases include skin diseases, gynecopathy, appendicitis, epilepsy, mental diseases, dental disease, eye disease, anemia, hyperthyroidism, vertigo, allergy, and other diseases.
Self-reported health status (category)	Self-reported health status of last year, including five categories: excellent, good, ordinary, bad, and poor.
Predisposing Variables	
Age (years)	The age of the rural resident.
Male (0/1)	"1" if the resident is a male, and "0" if female.
Education (category)	The highest education level, including six categories: not educated, primary school, middle school, high school, junior college or technical school, and college or above.
Enabling Variables	
NCMS Insurance (0/1)	"1" if the individual has participated in the New Rural Cooperative Medical Scheme (NCMS) the last year, and "0" if otherwise, including no insurance, or participating in the Urban Employee-Based Medical Insurance, Urban Resident-Based Medical Insurance, and other commercial insurance plans.
Family wealth index (0-10 scale points)	Family wealth index is constructed using a pooled principal component analysis based on household asset indicators, including television, car, motorcycles, washing machine, computer, fridge, water heater, and LPG stove. The index is rescaled to 0-10 scale points.
Per capita income of the village (Yuan in 2011 value, log)	Log transformation of the per capita income of the living village in 2011 value (1 USD = 6.29 Yuan, exchange rate in 2011).
Health Care Delivery System	
Village clinic equipment index (0-10 scale points)	Village clinic equipment index is constructed using a pooled principal component analysis based on village clinic equipment indicators, including high-temperature disinfection instrument, ultraviolet disinfection lamp, wound kit, diagnosis bed, sputum aspirator, treatment plate, contaminant tub, tongue depressor, tourniquet, cool bag, oxygen kit, and height-weight scale. The index is rescaled to 0-10 scale points. The maximum village clinic equipment index is used if more than one village clinic operates in the village.
Number of drugs available in village (log)	Log transformation of the number of drugs in inventory in local village clinics, including western drugs, Chinese patent drugs, and Chinese herbal drugs. The maximum number of drugs is used if more than one village clinics operates in the village.
Number of village doctors per 1000 population	Calculated using village doctors divided by the village population (per 1000 population).
The village has nationally-licensed doctors (0/1)	"1" if the living village has nationally licensed doctors or licensed assistant doctors, and "0" if otherwise.
Medical practicing years of village doctors (years)	The medical practicing years of village doctors working in this village. The average of the medical practicing years is calculated if more than one village doctor works in this village.
Distance to the nearest township health center (km)	Self-reported distance from the household to the nearest township health center (km).
Distance to the nearest county hospital (km)	Self-reported distance from the household to the nearest county hospital (km).

Note: the variables are categorized based on Andersen/Aday Health Behavior Model (1974)

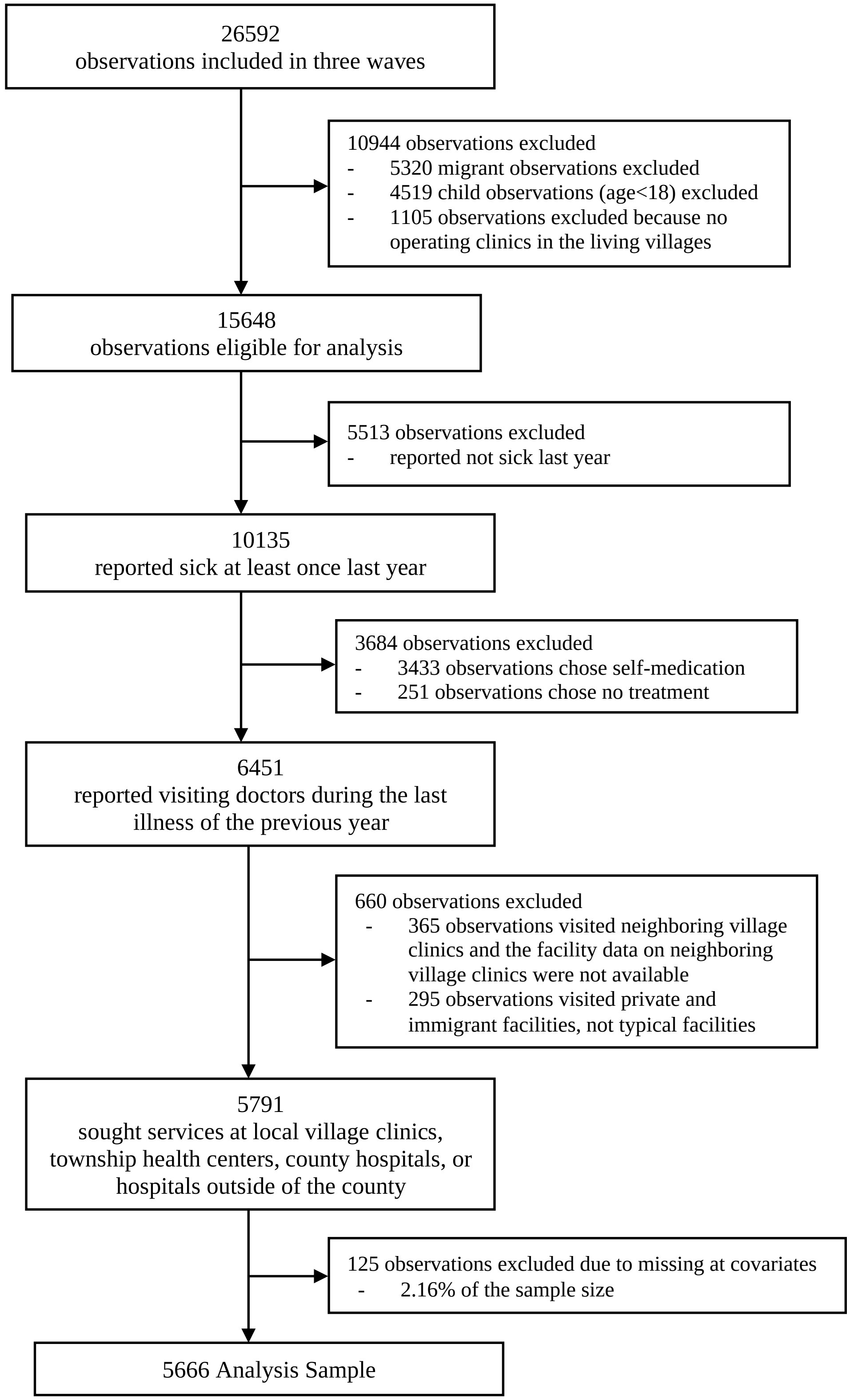


Figure A4 Sample Constraint

Table A5. Healthcare-seeking Behavior of Adult Rural Patients

	2011	2015	2018
Adult Rural Residents	**5589**	**4647**	**5412**
Sick in the past year (0/1)	3759 (67%)	2970 (64%)	3406 (63%)
Care-seeking Choice During Last Illness			
Number of Sick Individuals	**3759**	**2970**	**3406**
Visit doctor (0/1)	2543 (68%)	1942 (65%)	1966 (58%)
Self-medication (Pharmacy) (0/1)	1068 (28%)	956 (32%)	1409 (41%)
Did not seek treatment (0/1)	148 (4%)	72 (2%)	31 (1%)
Facility Choice during Doctor Visit			
Number of Patients Visiting Doctors	**2543**	**1942**	**1966**
Local Village Clinics (0/1)	1156 (45%)	685 (35%)	629 (32%)
Neighboring Village Clinics (0/1)	183 (7%)	110 (6%)	72 (4%)
Township Health Center (0/1)	396 (16%)	411 (21%)	379 (19%)
County Hospitals (0/1)	428 (17%)	480 (25%)	643 (33%)
Hospitals outside of the county (0/1)	203 (8%)	165 (8%)	216 (11%)
Others (Private or Immigrant facilities) (0/1)	177 (7%)	91 (5%)	27 (1%)

Note. This table presents healthcare-seeking behavior of rural adult residents, excluding migrants, children, and households from the villages without operating village clinics.

Table A6. Disease Type by Age Groups

Disease Type	Age Younger Than 50			Age Older Than 50		
	2011	2015	2018	2011	2015	2018
Acute Respiratory Infection (0/1)	67.7%	59.9%	59.1%	41.6%	37.6%	31.6%
Non-communicable Disease (0/1)	7.0%	11.2%	9.7%	20.0%	27.0%	26.1%
Infectious Disease (0/1)	0.2%	0.2%	0.4%	0.7%	0.5%	0.4%
Digestive System Disease (0/1)	4.8%	6.2%	7.2%	8.6%	7.2%	7.7%
Musculo-skeletal Disease (0/1)	4.2%	4.6%	6.8%	7.9%	8.3%	9.8%
Cerebral Disease (0/1)	0.7%	0.4%	0.6%	4.1%	6.0%	6.8%
Cancer (0/1)	0.4%	0.6%	0.6%	1.3%	1.4%	2.7%
Injury (0/1)	3.1%	4.0%	1.9%	3.2%	2.4%	3.2%
Other diseases (0/1)	11.8%	12.9%	13.6%	12.7%	9.6%	11.7%

Note. Non-communicable diseases include heart diseases, hypertension, diabetes, hyperlipemia, and chronic respiratory disease; Infectious diseases include TB, hepatitis, pertussis, meningitis, and diphtheria; Other diseases include skin diseases, gynecopathy, appendicitis, epilepsy, mental diseases, dental disease, eye disease, anemia, hyperthyroidism, vertigo, allergy, and other diseases.

Table A7. The Oaxaca-Blinder Decomposition with Bootstrapped Standard Errors

	2011 to 2018 (N=3958)			2011 to 2015 (N=3832)			2015 to 2018 (N=3542)		
	Estimates (1)	SE (2)	Explained Change (3)	Estimates (4)	SE (5)	Explained Change (6)	Estimates (7)	SE (8)	Explained Change (9)
Initial Proportion of VC Utilization	0.527	--	--	0.527	--	--	0.400	--	--
End Proportion of VC Utilization	0.340	--	--	0.400	--	--	0.340	--	--
Total Change	**-0.187**	--	--	**-0.127**	--	--	**-0.060**	--	--
Contribution of Explanatory Variables to Change									
Disease composition	-0.063***	(0.012)	33.7%	-0.030***	(0.010)	23.6%	-0.027**	(0.012)	45.0%
Health status	-0.005***	(0.002)	2.7%	-0.002	(0.002)	1.6%	-0.003	(0.002)	5.0%
Demographics	0.016***	(0.005)	-8.6%	0.006**	(0.003)	-4.7%	0.002	(0.002)	-3.3%
Education	0.001	(0.001)	-0.5%	-0.002	(0.002)	1.6%	0.002	(0.002)	-3.3%
Insurance	-0.001	(0.001)	0.5%	0.000	(0.001)	0.0%	-0.001	(0.001)	1.7%
Household wealth	-0.003	(0.004)	1.6%	-0.001	(0.005)	0.8%	0.001	(0.001)	-1.7%
Village economic level	-0.006	(0.017)	3.2%	0.011	(0.014)	-8.7%	0.012	(0.007)	-20.0%
Medical equipment availability	0.002	(0.004)	-1.1%	-0.000	(0.003)	0.0%	0.002	(0.004)	-3.3%
Drug availability	-0.037***	(0.012)	19.8%	-0.024***	(0.008)	18.9%	0.000	(0.009)	0.0%
Doctor availability	-0.006	(0.007)	3.2%	-0.012	(0.012)	9.4%	0.001	(0.003)	-1.7%
Doctor qualification	0.003	(0.003)	-1.6%	0.004	(0.005)	-3.1%	0.000	(0.002)	0.0%
Doctor medical practicing year	-0.009	(0.007)	4.8%	-0.002	(0.004)	1.6%	-0.002	(0.005)	3.3%
Distance to higher-tiered health facilities	0.001	(0.002)	-0.5%	0.001	(0.002)	-0.8%	0.000	(0.002)	0.0%
County fixed-effect	0.005	(0.006)	-2.7%	0.006	(0.008)	-4.7%	0.008	(0.007)	-13.3%
Explained Change by All Included Variables	**-0.103**	--	**55.1%**	**-0.045**	--	**35.4%**	**-0.007**	--	**11.7%**
Unexplained Change	**-0.083**	--	**44.4%**	**-0.082**	--	**64.6%**	**-0.053**	--	**88.3%**

*Note. The coefficients from a pooled sample of two waves are used in the decomposition estimation. Bootstrapped standard errors are reported to adjust the variability induced by the randomness of the predictors. The bootstrap sampling repeats 2000 times. * p<0.10, ** p<0.05, *** p<0.01*

Table A8. The Fairlie Non-linear Decomposition Using the Starting Wave Coefficients

	2011 to 2018 (N=3958)			2011 to 2015 (N=3832)			2015 to 2018 (N=3542)		
	Estimates (1)	SE (2)	Explained Change (3)	Estimates (4)	SE (5)	Explained Change (6)	Estimates (7)	SE (8)	Explained Change (9)
Initial Proportion of VC Utilization	0.527	--	--	0.527	--	--	0.400	--	--
End Proportion of VC Utilization	0.340	--	--	0.400	--	--	0.340	--	--
Total Change	**-0.187**	--	--	**-0.127**	--	--	**-0.060**	--	--
Contribution of Explanatory Variables to Change									
Disease composition	-0.060***	(0.004)	32.1%	-0.030***	(0.003)	23.6%	-0.025***	(0.003)	41.7%
Health status	-0.006***	(0.002)	3.2%	-0.003	(0.002)	2.4%	-0.001	(0.002)	1.7%
Demographics	0.016***	(0.004)	-8.6%	0.011***	(0.003)	-8.7%	-0.001	(0.002)	1.7%
Education	0.001	(0.001)	-0.5%	-0.001	(0.001)	0.8%	0.002**	(0.001)	-3.3%
Insurance	-0.001**	(0.001)	0.5%	0.001*	(0.001)	-0.8%	-0.001	(0.001)	1.7%
Household wealth	-0.001	(0.003)	0.5%	-0.002	(0.005)	1.6%	0.001	(0.002)	-1.7%
Village economic level	-0.006	(0.016)	3.2%	-0.004	(0.011)	3.1%	0.011**	(0.005)	-18.3%
Medical equipment availability	0.002	(0.002)	-1.1%	-0.000	(0.001)	0.0%	0.001	(0.002)	-1.7%
Drug availability	-0.032***	(0.008)	17.1%	-0.028***	(0.006)	22.0%	-0.008***	(0.002)	13.3%
Doctor availability	-0.009	(0.006)	4.8%	-0.008	(0.006)	6.3%	-0.000	(0.001)	0.0%
Doctor qualification	0.005***	(0.002)	-2.7%	0.004***	(0.001)	-3.1%	0.001	(0.001)	-1.7%
Doctor medical practicing year	-0.005	(0.005)	2.7%	-0.002	(0.002)	1.6%	-0.001	(0.003)	1.7%
Distance to higher-tiered health facilities	0.001	(0.001)	-0.5%	0.002**	(0.001)	-1.6%	0.000	(0.001)	0.0%
County fixed-effect	-0.001	(0.004)	0.5%	0.005	(0.004)	-3.9%	0.002	(0.004)	-3.3%
Explained Change by All Included Variables	**-0.096**	--	**51.3%**	**-0.055**	--	**43.3%**	**-0.018**	--	**30.0%**
Unexplained Change	**-0.091**	--	**48.7%**	**-0.072**	--	**56.7%**	**-0.042**	--	**70.0%**

Note. The coefficients from the starting wave are used in the decomposition estimation. Fairlie non-linear decomposition randomly orders the variables across decomposition replications to address path dependence. A total of 2000 decomposition replications are performed to approximate the decomposition estimates. The estimation model is the logit model.
** p<0.10, ** p<0.05, *** p<0.01*

Table A9 The Fairlie Non-linear Decomposition Using the Paneled Sample Only

	2011 to 2018 (N=3133)			2011 to 2015 (N=3058)			2015 to 2018 (N=2801)		
	Estimates (1)	SE (2)	Explained Change (3)	Estimates (4)	SE (5)	Explained Change (6)	Estimates (7)	SE (8)	Explained Change (9)
Initial Proportion of VC Utilization	0.545	--	--	0.545	--	--	0.423	--	--
End Proportion of VC Utilization	0.345	--	--	0.423	--	--	0.345	--	--
Total Change	**-0.200**	--	--	**-0.122**	--	--	**-0.078**	--	--
Contribution of Explanatory Variables to Change									
Disease composition	-0.071***	(0.004)	35.5%	-0.033***	(0.003)	27.0%	-0.032***	(0.002)	41.0%
Health status	-0.007***	(0.002)	3.5%	-0.004*	(0.002)	3.3%	-0.002	(0.002)	2.6%
Demographics	0.017***	(0.004)	-8.5%	0.006**	(0.002)	-4.9%	0.002	(0.002)	-2.6%
Education	0.000	(0.001)	0.0%	-0.002**	(0.001)	1.6%	0.001	(0.001)	-1.3%
Insurance	-0.001*	(0.000)	0.5%	0.001	(0.000)	-0.8%	-0.001	(0.001)	1.3%
Household wealth	-0.003	(0.003)	1.5%	-0.000	(0.004)	0.0%	0.000	(0.001)	0.0%
Village economic level	-0.009	(0.011)	4.5%	0.009	(0.009)	-7.4%	0.008***	(0.003)	-10.3%
Medical equipment availability	0.001	(0.001)	-0.5%	-0.001	(0.001)	0.8%	-0.000	(0.001)	0.0%
Drug availability	-0.039***	(0.006)	19.5%	-0.026***	(0.004)	21.3%	-0.010***	(0.002)	12.8%
Doctor availability	-0.006	(0.005)	3.0%	-0.015***	(0.005)	12.3%	0.001	(0.001)	-1.3%
Doctor qualification	0.002*	(0.001)	-1.0%	0.005***	(0.001)	-4.1%	0.000	(0.000)	0.0%
Doctor medical practicing year	-0.012***	(0.004)	6.0%	-0.007***	(0.002)	5.7%	-0.005**	(0.002)	6.4%
Distance to higher-tiered health facilities	-0.000	(0.001)	0.0%	0.002***	(0.001)	-1.6%	-0.001*	(0.001)	1.3%
County fixed-effect	0.002	(0.003)	-1.0%	0.005	(0.004)	-4.1%	0.006	(0.004)	-7.7%
Explained Change by All Included Variables	**-0.125**	--	**62.5%**	**-0.060**	--	**49.2%**	**-0.034**	--	**43.6%**
Unexplained Change	**-0.075**	--	**37.5%**	**-0.062**	--	**50.8%**	**-0.044**	--	**56.4%**

*Note. This table constrains the sample to households followed in all three waves. The coefficients from a pooled sample of two waves are used in the decomposition estimation. Fairlie non-linear decomposition randomly orders the variables across decomposition replications to address path dependence. A total of 2000 decomposition replications are performed to approximate the decomposition estimates. The estimation model is the logit model. * p<0.10, ** p<0.05, *** p<0.01*