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RESEARCH ARTICLE

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Selection and behavioral responses of health insurance subsidies in the long run: Evidence from a field experiment in Ghana

Patrick Opoku Asuming[1] | **Hyuncheol Bryant Kim**[2] | **Armand Sim**[3]

[1]University of Ghana Business School, Accra, Ghana

[2]Department of Economics, Hong Kong University of Science and Technology, Hong Kong, Hong Kong

[3]Centre for Development Economics and Sustainability, Monash University, Caulfield East, Victoria, Australia

Correspondence
Hyuncheol Bryant Kim.
Email: hbkim@ust.hk

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Abstract

We study the effects of a health insurance subsidy in Ghana, where mandates are not enforceable. We randomly provide different levels of subsidy (1/3, 2/3, and full) and evaluate the impact at 7 months and 3 years after the intervention. We find that a one-time subsidy increased insurance enrollment for all groups in both the short and long runs, but health care utilization in the long run increased only for the partial subsidy group. We find supportive evidence that ex-post behavioral responses rather than ex-ante selective enrollment explain the long-run health care utilization results.

KEYWORDS
health insurance, randomized experiments, selection, sustainability

JEL CLASSIFICATION
I1, H2

1 | INTRODUCTION

Many developing countries have been increasingly instituting social health insurance schemes (SHIs) to help mitigate the effects of adverse health shocks, especially for the poor (WHO, 2005, 2010).[1] SHIs offer low sign-up costs and generous benefits, but the take-up and retention rates of these schemes remain low in many countries (Fenny et al., 2016; Thornton et al., 2010; Wagstaff et al., 2016), especially among the poorest households (Acharya et al., 2013).

Achieving universal coverage or a high enrollment rate is important for risk pooling and maintaining the sustainability of SHIs. To ease their financial burden and sustain SHIs, some countries, such as Ghana and Indonesia, have introduced a contributory system with individual mandates (Banerjee et al., 2021). Enforcing mandates in this system is important because without such mandates, insurance can become financially unsustainable if those who are more ill or require more healthcare services selectively enroll in social health insurance. However, due to administrative constraints, governments in developing countries may find it difficult to successfully impose the mandates.

Recent studies have found that various efforts to promote health insurance enrollment and health care utilization have exerted a limited impact (Capuno et al., 2016; Thornton et al., 2010; Wagstaff et al., 2016).[2] Subsidies represent one of the few successful types of interventions to promote health insurance enrollment in developing countries (e.g., Baillon et al., 2022; Banerjee et al., 2021; Thornton et al., 2010). However, there are two important aspects of the effects of subsidy intervention that remain less understood. The first of these is the effects of subsidy level (price). Different levels of subsidies may attract people with different characteristics, and this selection may affect health care service utilization among the insured.[3] The screening effect of the subsidy level has been studied for a few health products and services, but it has not been intensively investigated for health insurance in a developing country setting, with the exception of Banerjee et al. (2021) work on Indonesia.[4]

The second aspect is related to the effects of receiving a temporary subsidy on long-run insurance enrollment and its consequences. The long-run effects are potentially ambiguous in theory. A temporary subsidy can reduce take-up in the long run if people consider the temporarily subsidized price as a reference point that could affect their future reservation prices (Kőszegi & Rabin, 2006; Simonson & Tversky, 1992). On the other hand, a temporary subsidy can increase demand in the long run for this type of experience good, that is, health insurance, if people using the subsidized good subsequently learn its value and benefits. Despite the importance of understanding the long-run effects of temporary subsidies, there is relatively scarce evidence regarding the application and evaluation of long-run health insurance enrollment in developing countries. Notable exceptions include Banerjee et al. (2021) and Baillon et al. (2022).

We complement the literature by studying the long-run impacts of different levels of one-time health insurance subsidies on enrollment, health care utilization, and health outcomes. Specifically, we randomly selected communities for subsidy intervention and further randomized subsidy levels—partial (one-third and two-thirds) and full—for 1-year insurance premiums and fees at the household level. We conducted a baseline survey and two follow-up surveys at 7 months (short run) and at 3 years (long run) following the initial intervention.

In addition to estimating enrollment effects, we analyze enrollment selection by subsidy level. Specifically, we examine *ex-ante* selection of insurance by investigating whether the subsidy induces those who are more ill and use more health care services to enroll in health insurance. Selection exists if compliers—those who self-select to enroll in health insurance in response to a partial or full subsidy—have greater *ex-ante* health risk or use more health care services than never-takers—those who do not enroll in health insurance regardless of subsidies. In theory, selection could be stronger in the partial subsidy group than in the full subsidy group because those who have to pay an insurance premium might enroll more selectively than those who do not.

We also evaluate potential *ex-post* behavioral responses by investigating whether those enrolled in health insurance with higher (lower) insurance prices are more (less) likely to utilize health care services (Chiappori & Salanié, 2013; Einav & Finkelstein, 2011).

Two sets of results emerge. First, we find significant increases in health insurance take-up, especially in the short run. Compared to the control group, the likelihood of short-run health insurance enrollment increased by 36.9, 47.6, and 51.7 percentage points for those receiving one-third, two-thirds, and full subsidies, respectively. Three years post-intervention, we still observed increased enrollment, albeit lower and marginally significant, with increases of 17.9, 14.3, and 20.4 percentage points for each respective subsidy group.

Second, we find evidence of *ex-ante* selection by subsidy (any subsidy vs. control), with compliers generally being sicker and utilizing more health care services at baseline than never-takers. While we do not detect varying selection by subsidy level (partial vs. full subsidy), we find that long-run health care service utilization increases only in the partial subsidy group but not in the full subsidy group. To reconcile these findings and gain a better understanding of the underlying mechanism, we analyze and detect *ex-post* behavioral responses (increased health care utilization) in the partial subsidy group but not in the full subsidy group.

Together, these results suggest that subsidies, especially partial subsidies, could negatively affect the financial sustainability of social health insurance programs.

Our study contributes to three strands of literature. First, our study is related to the literature on the impacts of subsidies or price interventions on selection in health insurance in developing countries. This topic has been underexplored in the literature, with a few recent exceptions (Banerjee et al., 2021; Fischer et al., 2023; Kinnan et al., 2020). We contribute to this literature in two ways. First, we provide different levels of insurance subsidies on enrollment, allowing us to study whether the characteristics of people who enrolled in health insurance vary by level of subsidy. Second, conducting two rounds of follow-up surveys within 3 years of the intervention allows us to study the selection dynamics, which is relatively rare within a developing country context.

Second, our study contributes to the literature on the sustainability of health intervention programs. This study is among the few to document evidence of the long-run effects of interventions on insurance enrollment and retention in a developing country, with some recent exceptions of (Baillon et al., 2022; Banerjee et al., 2021).[5] While the idea of promoting sustainability is attractive, it is difficult to achieve in practice. The challenges in promoting sustainable health insurance enrollment in developing countries could be even greater because health care services in developing countries are generally of low quality and reliability.[6] A few studies on this topic find mixed results on the effects of a one-time subsidy. In contrast to Kremer and Miguel (2007), who find limited evidence that providing a subsidy promotes the long-run adoption of worm treatment, and Chemin (2018), who finds a short-lived impact of a one-time subsidy on health insurance enrollment, Dupas (2014) finds that a one-time subsidy is effective in boosting long-run adoption of bed nets.[7]

Finally, our study contributes to the broad empirical literature on the effects of health insurance coverage on health care utilization and health status, which has thus far produced mixed evidence. Some studies find insignificant impacts of insurance coverage on health outcomes (Fink et al., 2013; King et al., 2009; Thornton et al., 2010), while others find positive impacts

(e.g., Conti & Ginja, 2023; Goodman-Bacon, 2018; Gruber et al., 2014; Miller et al., 2013).[8] In terms of out-of-pocket (OOP) expenses, some studies find no effects or adverse effects of insurance on such expenses (e.g., Fink et al., 2013; Nguyen, 2012; Thornton et al., 2010), while others find the opposite (e.g., Galárraga et al., 2010). Our study is among the first to examine the effects of insurance coverage on both short- and long-run health outcomes in a low-income setting, the existing literature largely focuses on short-run outcomes.[9]

The remainder of this paper is structured as follows. Section 2 outlines the research context. Section 3 describes the experimental design and data. Section 4 presents the empirical strategy, and Section 5 presents the main results. Section 6 concludes the paper.

2 | INSTITUTIONAL BACKGROUND

2.1 | National Health Insurance Scheme in Ghana

The National Health Insurance Scheme (NHIS) in Ghana was established by the National Health Insurance Act (Act 560) in 2003. Its aim is to improve the access and quality of basic health care services for all citizens, especially the poor and vulnerable (MoH, 2004). The law mandates that every citizen must enroll in at least one scheme. However, in practice, there are no penalties for those who do not enroll. Most of the 170 administrative districts of Ghana operate their own District Mutual Health Insurance Scheme (Gajate-Garrido & Owusua, 2013).[10] Each District Mutual Health Insurance Schemes (DMHIS) accepts and processes applications, collects premiums (and fees), provides membership identification cards, and processes claims from accredited facilities for reimbursement.

Annual means-tested premiums, which apply to informal sector workers, range from $5 to $32. However, due to the lack of information on household incomes, rural districts tend to charge lower premiums, while urban districts tend to charge higher premiums. Indigents, pregnant women, children under 18 years, and elderly individuals over 70 years are exempt from premiums but not from registration fees.[11] All members, except for indigents and pregnant women, are required to pay registration fees when they first register and when they renew. Those who do not renew their membership by the due date must pay penalties to renew their memberships.

The benefits package of the NHIS, which is the same across DMHISs, is very generous, although new members must wait for 3 months before they can enjoy the insurance benefits. As described in Table A1, the package covers (1) full outpatient and inpatient (surgery and medical) treatments and services, (2) full coverage for approved medications, (3) payments for approved referrals, and (4) all emergencies. The National Health Insurance Authority (NHIA) estimates that 95% of the disease conditions that affect Ghanaians are covered by the scheme (NHIA, 2010). Those who enroll do not pay deductibles or copayments for health care service utilization by law; however, according to the USAID (2016), health care providers often charge unauthorized fees that are inaccurately described as copayments.

Despite the low premiums and generous benefits provided by NHIS, enrollment remains low. By the end of 2010, the total active membership stood at 34% of the population (NHIA, 2011). Enrollment is particularly low among the poorest people. A 2008 nationwide survey found that only 29% of the individuals in the lowest wealth quintile were active members of the scheme, whereas 64% of the households in the highest quintile were active members (NDPC, 2009).

In addition to the lack of affordability, negative perceptions of the NHIS explain the low enrollment rate. For example, Alhassan et al. (2016) note that those enrolled in the NHIS generally feel as if they are not receiving good-quality health care because of, for instance, long wait times and the poor attitudes of health staff toward patients. Additionally, Fenny et al. (2016) observe that perceived quality of service and sociocultural factors, such as trust, the attitudes of health facility staff, and drug shortages, contribute to the low enrollment and retention rates in Ghana.

2.2 | Setting

This study was conducted in Wa West, a poor and remote rural district in northern Ghana (Figure A1). Wa West covers an area of approximately 5899 km^2 and had a population of approximately 81,000 in 2010. Its settlement patterns are highly dispersed, with most residents living in hamlets of approximately 100–200 people. This high dispersion, coupled with the poor road network, makes traveling within the district both difficult and expensive. The economy is largely agrarian, with over 90% of the population working as farmers. Estimates from the 2006 Ghana Living Standard Survey indicate that the average annual per-capita income and health expenditure in a rural savannah locality such as Wa West were approximately $252 and $26, respectively (GSS, 2008).

In the study area, even though community-based health and planning services have increased the accessibility to health care services,[12] there are only six public health centers and no tertiary health facilities. During the study period, the district had only 15 professional nurses and no medical doctor (Nang-Beifua, 2010). The district also has a high disease burden. The most common cause of outpatient visits in the region is malaria, which accounts for one-third of all outpatient visits. Other common causes of outpatient visits are acute respiratory tract infections and skin diseases.

The Wa West DMIHS was introduced in January 2007. In 2011, it charged a uniform premium of $5.46 (GHC 8.20) for adults (18–69) and a processing fee of $2.67 (GHC 4) for first-time members with a $0.60 (GHC 1) fee for renewals. Late renewals incur a fee of $1.30 (GHC 2) in addition to the full premiums for all years for which the membership was not renewed.[13] The baseline enrollment rate for the study sample in 2011 is 20%.

3 | RESEARCH DESIGN

In this section, we discuss the original study, data collection, definition and construction of key variables, descriptive statistics and the balance test of baseline characteristics.

3.1 | Interventions

We begin by discussing the original study aimed at analyzing the short-run outcomes (Asuming, 2013). Three different interventions were introduced to 4406 individuals from 629 households across 59 communities, namely, a subsidy for insurance premiums and fees (*Subsidy*), an information campaign on national health insurance (*Campaign*), and an option for individuals to sign up in their community rather than having to travel to the district capital (*Convenience*). Interventions were overlapping and randomized at the community level. Figure B1 summarizes our original research design.[14]

The *Subsidy* intervention was conducted in two stages. In the first stage, subsidies were randomly provided to households across communities. In the second stage, subsidy levels were randomized at the household level within the *Subsidy* communities as follows: one-third ($2.67), two-thirds ($5.40), or full ($8.13) subsidy (see Figure 1). Subsidies were provided in the form of vouchers, which were distributed between November 2011 and January 2012, were valid for two months, and were redeemable at the Wa West DMHIS center.[15]

The subsidy vouchers specified the names, ages, and sexes of all household members, the expiration date, and the place of redemption.[16] Households that did not receive a full subsidy were informed of the additional amount needed to register all

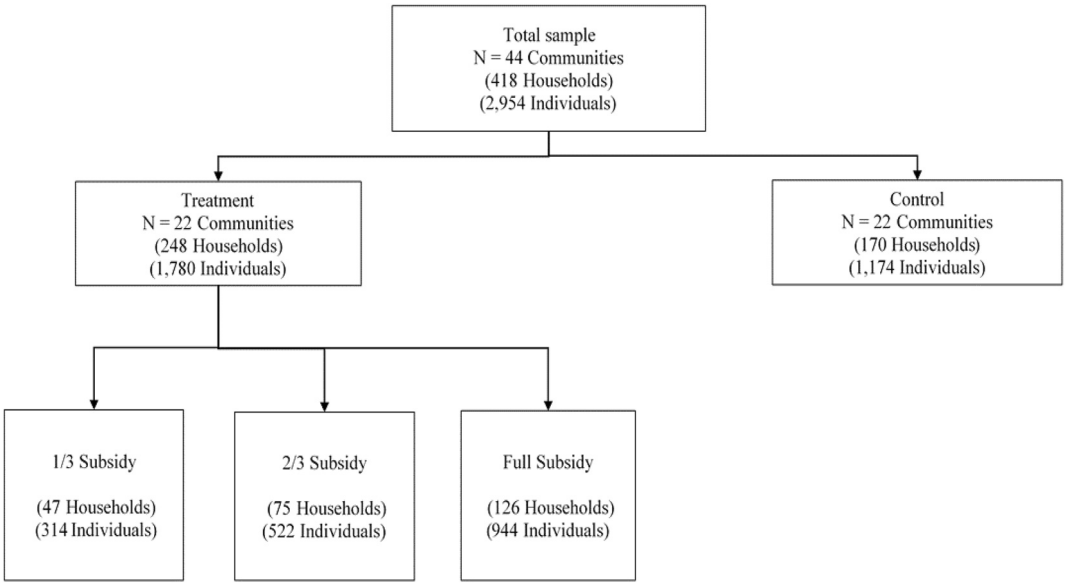

FIGURE 1 Study design.

members. Although a subsidy was provided at the household level, enrollment had to be specified for each household member. Households did not necessarily insure all members.

We extended the original study by implementing a long-term follow-up survey and focused only on the *Subsidy* intervention.[17] To formally support our approach, we conducted two empirical exercises. First, we conducted complementarity tests between *Subsidy* and other treatments, that is, to test whether the treatment effect of the whole (e.g., *Subsidy* + *Campaign*) is greater than the sum of its parts: *Subsidy* and *Campaign*. The results, shown in Appendix Table B1, rule out complementarity effects between all interventions suggesting that the *Subsidy* intervention is independent of the other interventions.[18] We also find that eight complementarity tests fail to reject the null hypothesis of no complementarity at the 5% level. Together, this empirical exercise shows that obtaining the unbiased causal effects of the *Subsidy* intervention does not require complementarity between *Subsidy* and the other treatments.

Second, we restrict the sample to the control and *Subsidy* only groups (i.e., excluding *Subsidy* + *Campaign*, *Subsidy* + *Convenience*, and *Subsidy* + *Campaign* + *Convenience*) to investigate the cleaner effects of subsidy variation, that is, to show that the effects are driven by the *Subsidy* intervention.[19] We provide the estimation results in Appendix Tables B2 (effects on enrollment), B3 and B4 (short- and long-run effects on health care utilization). Overall, the results of these two exercises lend support to our approach, and the interpretation of our main findings and conclusion holds.[20]

3.2 | Data collections

Given that we are primarily interested in examining the impacts of subsidy, our analysis is restricted to respondents who received a subsidy intervention (*Subsidy*, *Subsidy* + *Campaign*, *Subsidy* + *Convenience*, and *Subsidy* + *Campaign* + *Convenience*) and those who did not receive any intervention (control group). Respondents that received campaign-only (*Campaign*) and convenience-only (*Convenience*) interventions are excluded. In total, the main sample includes 2954 individuals from 418 households in 44 communities.[21] We conducted the baseline survey in September 2011 and implemented the intervention in October 2011. We conducted two follow-up surveys at 7 months and 3 years after the intervention.[22] The baseline survey collected information on the demographics, employment, health status, health care service utilization, NHIS enrollment, and health behaviors of all household members.

The first follow-up survey collected information on health care service utilization, health status, and health behaviors. In the second follow-up survey, we collected sets of information like those in the first follow-up survey but with greater detail to improve the quality of the data. For example, we asked for specific dates and the respondent's status since the first follow-up for up to three episodes of several important illnesses, such as malaria, acute respiratory diseases, and skin diseases. As a result, there are some differences in the construction of short- and long-run utilization measures that prevent a direct comparison of health care service utilization and health status in these survey periods.[23]

The main outcome variables, as measured at the individual level, are health insurance enrollment, health care service utilization, and self-reported health status. Health care service utilization is measured by health facility visits in the last 4 weeks and in the last 6 months. Health status is measured by the number of illness days in the last 4 weeks, the indicator and the number of days an individual was unable to perform normal daily activities due to illness, and self-rated health status.[24] The measure of inability to perform normal daily activities is essentially similar to the measure of activities of daily living (ADL), which is commonly used in the literature as an objective measure for health status.[25]

The attrition rate in the first follow-up survey was relatively low (5%) but increased in the second follow-up survey (21%), which may raise some concerns with the possibility of differential attrition by treatment. To address this issue, we test for differential attrition in the short and long runs. Appendix Table A2 shows no indication of differential attrition by treatment status (Panel A) or subsidy level status (Panels B and C).[26] Next, we examine whether baseline characteristics of attriters in the short and long runs differ by treatment status. To test this, we regress baseline characteristics on the indicators of attrition, treatment status (partial subsidy vs. control, full subsidy vs. control, and partial subsidy vs. full subsidy), and their interaction. Only 18 (15%) out of 120 coefficients of the interaction terms are statistically significant at the conventional level, as reported in Table A3. Moreover, only 6 out of 60 are statistically significant at the 10% level for the long-run analysis, which is the main focus of this study. Importantly, we control for these baseline characteristics in all regression specifications, which can help remove some biases from some sample imbalance caused by attrition (Athey & Imbens, 2017). Together, these results suggest that attrition is not a main concern in this study.

3.3 | Baseline characteristics and balance test

Table 1 presents the summary statistics of baseline characteristics and balance tests between the intervention and control groups. Panels A and B report the means of the baseline control (socioeconomic and community) and outcome variables. Columns 1–5 report the means of the baseline characteristics for all respondents, the control group, and the treatment groups. The average respondent is approximately 24 years old, and 48% are male. Approximately 20% were enrolled in the NHIS at baseline, and 36% had registered with the scheme at some point. In terms of health characteristics, 12% reported a sickness or injury in the last 4 weeks, approximately 4% visited a health facility in the last month, and 14% had made a positive OOP health expenditure. The average household lived within 5.4 km of a health facility and 20 km from the district capital.

Columns 3–5 present the results from the regressions of each variable on control and subsidy level indicators. Only 2 out of 66 coefficients across all balance tests are statistically significant at the 5% level, which is what we would expect to occur by chance. We also compare the baseline differences between each subsidy level group in Columns 7–9. Only 1 out of 66 coefficients across all balance tests are statistically significant at the 5% level. Overall, these results suggest that our randomization is successful in creating balance across the control and treatment groups.[27]

3.4 | Health insurance enrollment pattern

In Appendix Table A5, the number of people in each survey round is displayed based on their enrollment status. This information can be useful in understanding the dynamic patterns of health insurance enrollment over both the short and long runs, including the acquisition and retention of insurance based on initial health status and healthcare utilization. We find that long-run enrollment is driven by people who retained their insurance from a previous round. For example, among 865 (=172 + 33 + 470 + 190) people who enrolled in the long run, only 190 (22%) enrolled neither in the baseline nor in the short run.

Appendix Table A6 presents evidence regarding the general selection pattern in health insurance enrollment by health status and health care utilization regardless of subsidy. Panel A examines selective retention. We restrict the sample to those who enrolled at baseline (Panels A1 and A2) and in the first follow-up (Panel A3) and examine whether future enrollment differs by health status and health care utilization. Similarly, we study selective new enrollment with a restricted sample of those who did not enroll at baseline (Panels B1 and B2) or at the first follow-up (Panel B3). We find some evidence of selective retention; those who are more ill are more likely to retain their insurance membership. We also find some evidence of selective enrollment based on health care utilization (Panel B3).

4 | ESTIMATION FRAMEWORK

To measure the effects of our intervention on various outcomes, we estimate the following reduced-form intent-to-treat (ITT) effect of each level of subsidy:

$$y_{ihc} = \gamma_0 + \gamma_1 1/3\,\text{Subsidy}_{ihc} + \gamma_2 2/3\,\text{Subsidy}_{ihc} + \gamma_3 \text{Full Subsidy}_{ihc} + \theta X_{ihc} + \delta Z_{hc} + \omega V_c + \epsilon_{ihc} \quad (1)$$

where y_{ihc} denotes the outcomes for individual i of household h in community c. The outcomes of interest include NHIS enrollment and health care service utilization. X_{ihc} denotes a vector of baseline individual covariates, such as indicator variables for age, gender, religion, ethnicity, schooling, and past enrollment in health insurance. Household covariates Z_{hc} include household size and a wealth index indicator (poor third, middle third, and rich third).[28] Community covariates V_c include distance to the nearest health facility and to the NHIS registration center.[29] We also control for a baseline measure of the dependent variable to improve precision. The results are robust when we exclude the baseline controls (results not shown). Estimations employ a linear probability model. For each outcome, we present its short- and long-run estimations.

Our parameters of interest, γ_1, γ_2, and γ_3, capture the effects of being offered one-third, two-thirds, and full subsidies, respectively. However, given that the main sample includes individuals receiving both a subsidy and other interventions (campaign and convenience), these effects may not be solely attributed to the subsidy even though Table B1 demonstrates a lack of complementarity effects between subsidy and other interventions.[30]

We cluster standard errors at the community level to account for possible correlation in the error terms within the same community.[31] We also perform 1000 draws of a wild-cluster bootstrap percentile t-procedure suggested by Cameron

TABLE 1 Baseline summary statistics and randomization balance.

	Mean		Difference between subsidy level and control				Difference between each subsidy level		
	All	Control	One-third	Two-thirds	Full	*N*	One-third versus two-thirds	One-third versus full	Two-thirds versus full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Control variables									
Age (years)	23.780	24.313	1.180	−0.775	−1.620	2954	1.955	2.800	0.844
Male	0.481	0.475	0.009	−0.010	0.022	2954	0.019	−0.013	−0.031
Christian	0.417	0.373	0.073	0.102	0.058	2954	−0.029	0.015	0.044
Dagaaba ethnic group	0.517	0.458	0.153	0.208	0.017	2954	−0.055	0.136	0.191
Has some formal education	0.335	0.337	−0.022	−0.015	0.009	2954	−0.007	−0.031	−0.025
Household size	8.703	8.454	−0.187	0.051	0.813	2953	−0.238	−0.999	−0.761
Household assets (principal component score)	0.601	0.266	0.580	0.269	0.705**	2953	0.311	−0.126	−0.436
Distance to district insurance office (km)	20.010	20.37	4.347	3.447	−4.466	2954	0.900	8.812	7.912
Distance to nearest health facility (km)	5.394	5.166	0.221	−0.687	1.017	2954	0.908	−0.796	−1.704**
Ever enrolled in NHIS	0.358	0.302	0.179**	0.084	0.071	2954	0.096	0.108	0.012
Panel B: Baseline values of outcome variables									
Enrollment	0.198	0.197	0.039	0.041	−0.030	2954	−0.002	0.069	0.071
Ill in the last 4 weeks	0.123	0.105	0.039	0.048	0.016	2954	−0.010	0.023	0.032
Number of sick days in the last 4 weeks	0.918	0.846	0.505	0.208	−0.056	2927	0.296	0.560	0.264
Could not do normal activities in the last 4 weeks	0.076	0.060	0.011	0.039	0.023	2919	−0.028	−0.012	0.016
No. of days could not perform normal activities in the last 4 weeks	0.544	0.480	0.134	0.138	0.079	2815	−0.004	0.055	0.060
Visited health facility in the last 4 weeks	0.039	0.036	0.033	0.023	−0.015	2435	0.010	0.048	0.038
Visited health facility in the last 6 months	0.074	0.074	0.025	0.008	−0.014	2954	0.016	0.038	0.022
Number of health facility visit in the last 4 weeks	0.066	0.063	0.062	0.042	−0.036	2443	0.020	0.098	0.078*
Visited health facility for malaria treatment in the last 4 weeks	0.010	0.011	−0.004	0.002	−0.004	2435	−0.006	−0.0005	0.006
Made out of pocket expense in the last 6 months	0.136	0.133	−0.009	0.059	−0.021	2954	−0.067	0.012	0.079*
Standardized health care utilization	0.000	−0.001	0.024	0.017	−0.016	10,267	0.007	0.040	0.034
Standardized health status	0.000	−0.011	0.026	0.029	0.011	8661	−0.003	0.014	0.017

Note: Columns 1 and 2 report mean of all respondents and control group. Columns 3–5 present results from regressions of each variable on control and subsidy level indicators (1/3, 2/3, and full). Column 6 reports total number of observations. Columns 7–9 present results from separate regressions of each variable on one-third and two-thirds subsidy levels (Column 7), on one-third and full subsidy levels (Column 8), and on two-thirds and full subsidy levels (Column 9). Robust standard errors are clustered at community level.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

et al. (2008) to address concerns about a small number of clusters, which could lead to downward-biased standard errors (Bertrand et al., 2004; Cameron et al., 2008).

Because we estimate Equation (1) for many different outcome variables in health care utilization and health status domain, a multiple hypothesis testing problem may occur. The probability that we incorrectly reject at least one null hypothesis is larger than the conventional significance level. We address this concern using two methods.

First, we group outcome variables into a domain and take the average standardized treatment effect in each domain, as suggested by Kling et al. (2007) and Finkelstein et al. (2012).[32] For the health care utilization domain, we group four outcome measures, including intensive and extensive measures of health facility visits in the last 4 weeks and last 6 months. For the health status domain, we group four outcomes including self-rated health status, number of days of illness, inability to perform normal activities, and the number of days lost to illness. Components of the standardized outcome move in the same direction.

Second, we apply the free step-down resampling procedure to adjust the family-wise error rate, that is, the probability of incorrectly rejecting one or more null hypotheses within a family of hypotheses (Westfall & Young, 1993). Family-wise adjusted p-values of each family are obtained from 10,000 simulations of estimations.[33]

5 | RESULTS

5.1 | Impacts on insurance enrollment

Figure 2 shows the enrollment rates of the control and treatment groups at the baseline, short-run follow-up, and long-run follow-up surveys by level of subsidy. In general, it shows that the enrollment rate increases with subsidy level in the short run, but these impacts became attenuated over time. We observe the largest incremental increase in enrollment rate between receiving zero (control group) and receiving a one-third subsidy in the short run but smaller incremental increases at higher subsidy levels. In the long run, the treatment group is still more likely to enroll in health insurance, but the differences among the one-third, two-thirds, and full subsidy groups become insignificant.

Table 2 presents the formal regression results. We present robust standard errors in parentheses and two-tailed wild cluster bootstrap p-values in square brackets. Our results show that the effects on enrollment are attenuated but sustained over time. Column (1) of Panel A shows that overall, the subsidy intervention increases short-run insurance enrollment by 44.6 percentage points (164%). Column (2) shows that long-run enrollment also increases by 16.8 percentage points (72%), on average, although it is marginally significant (p-values = 0.051; wild-cluster bootstrap p-values = 0.1).

In terms of subsidy levels, receiving a one-third, two-thirds, and full subsidy is associated with, respectively, a 36.9, 47.6, and 51.7 percentage points higher likelihood of enrolling in insurance than the control group in the short run. The enrollment effects decrease in the long run, but they are still higher than the enrollment of the control group. Receiving a one-third, two-thirds, and full subsidy is associated with, respectively, 17.9, 14.3, and 20.4 percentage points higher likelihood of enrolling in insurance than the control group. Although the long-run effects are economically large, these effects are only marginally significant in general.[34] In addition, there is no significant difference among the effects of receiving different subsidy levels.

We find that our respondents are highly sensitive to the price of health insurance in the short run, as reflected by relatively large price elasticities. For example, receiving a full subsidy offer—reduced price of insurance membership from $8.13 to

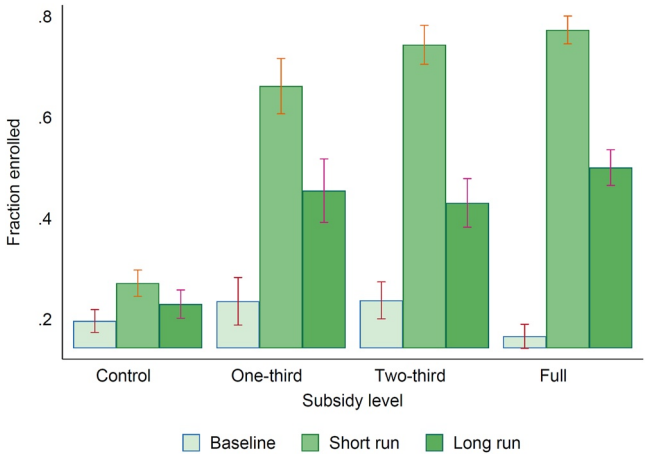

FIGURE 2 Enrollment rate by Subsidy level at baseline, short run, and long run. This figure shows means of enrollment rates of each subsidy-level group at baseline, short run (7 months after the intervention), and long run (3 years after the intervention). Sample includes those who received subsidy and the control group. The vertical lines indicate 95% confidence intervals. Standard errors are not clustered. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Effects of subsidy (level) on National Health Insurance Scheme (NHIS) enrollment.

	Enrollment	
	Short-run	**Long-run**
	(1)	**(2)**
Panel A		
Any subsidy	0.446***	0.168*
	(0.054)	(0.084)
	[0.000]	[0.103]
R-squared	0.359	0.186
Panel B		
Partial subsidy	0.430***	0.158*
	(0.055)	(0.082)
	[0.000]	[0.117]
Full subsidy	0.508***	0.207**
	(0.060)	(0.102)
	[0.000]	[0.125]
R-squared	0.361	0.187
Panel C		
1/3 subsidy	0.369***	0.179**
	(0.073)	(0.087)
	[0.001]	[0.115]
2/3 subsidy	0.476***	0.143
	(0.060)	(0.087)
	[0.000]	[0.156]
Full subsidy	0.517***	0.204*
	(0.057)	(0.102)
	[0.000]	[0.105]
R-squared	0.364	0.188
Number of observations	2785	2257
Mean	0.555	0.383
Control group mean	0.272	0.233
p-values on test of equality:		
Partial subsidy = full subsidy	0.120	0.435
1/3 subsidy = 2/3 subsidy	0.122	0.585
1/3 subsidy = full subsidy	0.014	0.702
2/3 subsidy = full subsidy	0.448	0.408

Note: All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. *p*-values for the equality of effect estimates for various pairs of treatment groups are also presented. Robust standard errors clustered at community level are reported in parentheses. Wild-cluster bootstrap *p*-values are reported in square brackets.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

$0—leads to a sharp increase in the demand for health insurance from 27.2% to 81.0%, indicating a price elasticity of roughly −0.50.[35] These results fall within the range of the elasticity of health insurance in developing countries, such as India, −0.33 (Kinnan et al., 2020), and Pakistan, −0.6 (Fischer et al., 2023), as well as within the range of those in developed countries (Pendzialek et al., 2016).[36] This similarity in elasticity estimates across various socio-economic contexts lends some credibility to our study and highlights the highly price-sensitive nature of health insurance demand regardless of the level of development.

Our finding that larger subsidies may lead to higher health insurance enrollment corresponds to the findings of studies in both developed and developing countries (Banerjee et al., 2021; Finkelstein et al., 2019). Specifically, we find a large incremental increase in enrollment between zero and the one-third subsidy (full and two-thirds price) but no significant difference

between having to pay nothing (received full subsidy) and small amount of money (received two-thirds subsidy) in the short run. This seems to contradict zero price theory, which states that when a good is offered at zero cost, individuals perceive it as not only being cost-free but also as providing additional benefits (Shampanier et al., 2007). Indeed, several studies find a larger decrease between zero and small nonzero prices in the demand for bed nets (Dupas, 2014) and HIV testing (Thornton, 2008). Our study differs from them in that our intervention focuses on the level of subsidy rather than the level of price, and therefore, the largest response to the intervention occurs between zero and a small (one-third) subsidy. This difference can potentially be explained by framing effects theory (Tversky & Kahneman, 1981).[37]

5.2 | Selection into health insurance by subsidy (level)

If subsidies induce people with greater ex ante health risks, that is, those who are more ill and use more health care services, to enroll in health insurance, it can threaten the financial sustainability of insurance programs. To investigate this issue, we examine selective enrollment into insurance based on the complier characteristics analysis framework following Almond and Doyle (2011) and Kim and Lee (2017). In this approach, we compare the baseline health and health care utilization characteristics of compliers, always-takers, and never-takers. The impacts we estimate are driven by compliers who enroll in health insurance in response to our subsidy intervention in the short and long runs. Therefore, we are particularly interested in comparing compliers and never-takers.[38]

To begin, we first define a binary variable T, an indicator for whether an individual is assigned to the treatment group (*Subsidy*). Next, we define a binary variable H, an indicator for whether an individual is enrolled in health insurance. Lastly, we define H_T as the value H would have if T were either 0 or 1. Hence, $\mathrm{E}(X|H_1 = 1)$ presents the mean value characteristics of treated individuals who enrolled in health insurance. Under the assumption of existence of the first stage, monotonicity, and independence, $\mathrm{E}(X|H_1 = 1)$ can be written as:

$$\begin{aligned}\mathrm{E}(X|H_1 = 1) = &\mathrm{E}(X|H_1 = 1, H_0 = 1) \cdot P(H_0 = 1|H_1 = 1) \\ &+ \mathrm{E}(X|H_1 = 1, H_0 = 0) \cdot P(H_0 = 0|H_1 = 1)\end{aligned} \tag{2}$$

Equation (2) implies that $\mathrm{E}(X|H_1 = 1)$ is a sum of always-takers and compliers components. $\mathrm{E}(X|H_1 = 1, H_0 = 0)$ represents the characteristics of compliers. $\mathrm{E}(X|H_1 = 1, H_0 = 1) = \mathrm{E}(X|H_0 = 1)$ holds from the monotonicity assumption. $P(H_0 = 1)$, the proportion of always-takers, and $P(H_1 = 0)$, the proportion of never-takers, can be directly measured from the sample. $P(H_0 = 1)$, the proportion of always-takers can be thus measured by P_a, the proportion of insurance takers in the control group. Similarly, the proportion of never-takers, $P(H_1 = 0)$, can also be measured by P_b, the proportion of insurance non-takers in the treatment group. The proportion of compliers is 1-P_a-P_b. Therefore, $P(H_0 = 0|H_1 = 1)$ and $P(H_0 = 0|H_1 = 1)$ are $\frac{P_a}{P_c + P_a}$ and $\frac{P_c}{P_c + P_a}$, respectively.[39] By rearranging Equation (2), the characteristic of compliers can be calculated as follows:

$$\mathrm{E}(X|H_1 = 1, H_0 = 0) = \frac{P_c + P_a}{P_c} \times \left[\mathrm{E}(X|H_1 = 1) - \frac{P_a}{P_c + P_a} \times \mathrm{E}(X|H_0 = 1)\right] \tag{3}$$

Table 3 presents the summary statistics of the baseline standardized health status and health care utilization of compliers, always-takers, and never-takers for short-run (Columns 1–3) and long-run selection (Columns 7–9).[40] We calculate the complier characteristics of any subsidy group in Panel A. We calculate the complier characteristics of the partial subsidy group by excluding the full subsidy group from the sample (Panel B). Similarly, we calculate the complier characteristics of the full subsidy group by excluding the partial subsidy group from the sample (Panel C). Columns 4–6 report the t-statistics for the mean comparison of each group in the short run. Columns 10–12 report similar statistics in the long run.

When comparing compliers to never-takers, we observe that subsidy intervention induced individuals who were more ill at the baseline to enroll in the short and long runs (Columns 5 and 11), and the selection effect becomes larger in the long run. Similarly, we observe selection based on baseline health status for the partial and full subsidy groups in Panels B and C.[41]

Next, we explore differential selection between the partial and full subsidy groups, as proposed by Kim and Lee (2017). We restrict the sample to those who enrolled in health insurance among the full and partial subsidy treatment groups. Since we restrict our sample to enrollees in the treatment group, which consists of compliers and always-takers, any difference between full and partial subsidy groups in the restricted sample results from the compositional changes of compliers.

Table 4 presents the regression results of the standardized measures of baseline health status and health care utilization on the full subsidy indicator.[42] In each panel, we present results on selection based on health status and health care utilization

TABLE 3 *Ex-ante* selection by Subsidy (level): Characteristics of compliers, always-takers, and never-takers.

	Short run						Long run					
	Mean			*t*-stat			Mean			*t*-stat		
	Complier	Always	Never	C = A	C = N	A = N	Complier	Always	Never	C = A	C = N	A = N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Control versus any subsidy												
Proportion	47.40	27.10	25.50				24.26	23.01	52.73			
Baseline standardized health status	0.0100	−0.0073	−0.0032	5.19	4.91	−0.95	0.0147	0.0141	−0.0063	0.09	9.61	2.91
Baseline standardized health care utilization	−0.0017	0.0077	−0.0137	−1.07	2.31	2.10	−0.0102	0.0401	−0.0147	−3.90	1.11	4.05
Panel B: Control versus partial subsidy												
Proportion	44.22	27.15	28.63				20.96	23.01	56.03			
Baseline standardized health status	0.0142	−0.0073	0.0024	6.45	2.88	−1.85	0.0229	0.0141	−0.0030	1.31	7.43	2.28
Baseline standardized health care utilization	0.0250	0.0027	0.0042	2.35	3.17	0.53	0.0157	0.0401	0.0021	−1.89	1.87	2.56
Panel C: Control versus full subsidy												
Proportion	50.20	27.15	22.65				27.05	23.01	49.94			
Baseline standardized health status	0.0068	−0.0073	−0.0096	4.22	4.72	0.46	0.0094	0.0141	−0.0094	−0.71	7.01	3.27
Baseline standardized health care utilization	−0.0252	0.0077	−0.0323	−3.77	1.50	4.03	−0.0266	0.0401	−0.0316	−5.18	1.49	5.36

Note: This table presents the mean baseline characteristics of compliers, always-takers, and never-takers, which are estimated from Equation (3). Columns 4–6 and 10–12 present the *t*-statistics from the two-sample *t*-test comparing compliers with always-takers, compliers with never-takers, and always-takers with never-takers, respectively.

at baseline. Panels A and B provide results on selection by subsidy level in the short and long runs, respectively. We find no evidence on (*ex-ante*) selection by subsidy level based on baseline characteristics.

5.3 | Impacts on health care service utilization

Table 5 presents the effects on health care services utilization in the short run. Column 5 presents average standardized effects, and the long-run effects are presented in Table 6. We find that receiving subsidies leads to an increase in the utilization of health care services in the long run (Panel A). Interestingly, we find increased health care utilization only for the partial subsidy group in the long run (Panels B and C) even though we find no evidence of impacts on enrollment rate and selection by health status or health care utilization between the partial and full subsidy groups (Tables 2 and 4).

Next, we investigate the correlation between insurance premiums and health care utilization to explore possible *ex-post* behavioral responses (Chiappori & Salanié, 2013; Einav & Finkelstein, 2011). We first restrict the sample to enrollees in the full and partial subsidy treatment groups. This allows us to compare the compliers of the partial group with those of the full subsidy group, as we do in Table 4. We then regress health status and health care utilization measured at the follow-up surveys

TABLE 4 Selection by Subsidy level (Partial vs. Full Subsidy): Baseline standardized health status and health care utilization among enrollees.

	Coefficient	Std. Error	*N*	*R*-squared
Independent variable: Received full subsidy	**(1)**	**(2)**	**(3)**	**(4)**
Panel A: Selection in the short run				
Sample: Enrolled in the short run				
Baseline standardized health status	0.011	(0.020)	7314	0.006
Baseline standardized health care utilization	−0.024	(0.033)	4515	0.010
Panel B: Selection in the long run				
Sample: Enrolled in the long run				
Baseline standardized health status	0.021	(0.034)	3886	0.013
Baseline standardized health care utilization	0.026	(0.045)	2381	0.024

Note: This table reports estimation results of running separate regressions of baseline enrollment, health status (standardized) and health care utilization (standardized) on an indicator variable that takes value of one if receiving full subsidy and zero if receiving partial subsidy. Sample is restricted to enrollees who received partial and full subsidy. Panels A and B summarize regression results when sample is restricted to those who enrolled in the short run. Robust standard errors clustered at community level reported in parentheses.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

on an indicator of full subsidy. Table 7 shows that those attracted by partial subsidies are more likely to use health care services in the long run—but not in the short run—than are those attracted by full subsidies.

These ex-post behavioral responses are rather surprising because the long-run impacts on enrollment are similar across subsidy groups. While these results are somewhat consistent with the findings reported in Tables 5 and 6, where health care utilization increased only in the long run and only for the partial subsidy group, there is a caveat. Table 7 only reports results for those who enrolled, that is, treatment on the treated results, while Tables 5 and 6 report ITT results. We speculate that this behavior may be due to learning among those with health insurance, as familiarity with insurance benefits and healthcare services could potentially increase usage in the long run.[43] While it would be interesting to further investigate the main reasons as to why these behaviors emerge in the long run, our data do not allow us to do so.

5.4 | Other outcomes

Next, we study the impacts on OOP expenses and subjective health status. We find limited evidence that health insurance prevents OOP expenses in both the short and long runs (Table A12). There are a few possible explanations for this finding. First, as we described earlier, most services are free under the NHIS, but health care providers often charge unauthorized fees miscategorized as copayments. Second, medicine is often in short supply at public health centers, and those who receive a diagnosis purchase medicine from a private pharmacy. Third, those without health insurance often use traditional or herbal medicine, which is inexpensive, and therefore, substitution from traditional medicine to formal health care does not decrease OOP expenses.

We find mixed evidence regarding the effects of intervention on subjective health status. Appendix Tables A13 and A14 present the effects on health status in the short and long runs (Columns 1–5). Panel A of Table A13 shows that insurance coverage improves health status in the short run. However, Panel A of Table A14 shows that the short-run positive health effect seems to disappear in the long run despite increased health insurance enrollment and health care service utilization, as shown in Tables 2 and 6. We even find negative health effects on the number of sick days and daily activities in the long run (Columns 2–4 of Table A14).[44]

6 | CONCLUSION

Many governments in developing countries aim to increase health insurance enrollment and ultimately achieve universal coverage. To achieve this goal, they offer low sign-up costs and generous benefits, but enrollment and retention rates remain low. Due to administrative constraints, governments find it difficult to impose mandates and enforce enrollment in health insurance.

TABLE 5 Effects on healthcare services utilization (short run).

	Short run				
	Visited health facility in last 4 weeks	Visited health facility in last 6 months	# of visits in last 4 weeks	Visited facility for malaria treatment in the last 4 weeks	Standardized treatment effects
	(1)	(2)	(3)	(4)	(5)
Panel A					
Any subsidy	−0.004	0.005	−0.0002	0.006	0.003
	(0.012)	(0.020)	(0.023)	(0.008)	(0.012)
	[0.725]	[0.802]	[0.992]	[0.457]	
	{0.973}	{0.973}	{0.993}	{0.863}	
R-squared	0.106	0.132	0.066	0.074	0.063
Panel B					
Partial subsidy	−0.007	0.007	−0.002	0.008	0.002
	(0.013)	(0.019)	(0.024)	(0.009)	(0.012)
	[0.606]	[0.731]	[0.929]	[0.400]	
	{0.898}	{0.923}	{0.943}	{0.808}	
Full subsidy	0.009	−0.001	0.008	0.0003	0.011
	(0.022)	(0.031)	(0.038)	(0.012)	(0.021)
	[0.700]	[0.965]	[0.842]	[0.981]	
	{0.984}	{0.999}	{0.997}	{0.999}	
R-squared	0.107	0.132	0.066	0.074	0.063
Panel C					
1/3 subsidy	0.001	0.004	−0.010	0.009	0.006
	(0.017)	(0.022)	(0.024)	(0.011)	(0.014)
	[0.958]	[0.835]	[0.698]	[0.480]	
	{0.978}	{0.978}	{0.956}	{0.885}	
2/3 subsidy	−0.014	0.008	0.004	0.007	−0.002
	(0.014)	(0.023)	(0.029)	(0.010)	(0.013)
	[0.381]	[0.738]	[0.877]	[0.485]	
	{0.786}	{0.920}	{0.920}	{0.838}	
Full subsidy	0.007	−0.001	0.010	0.0002	0.010
	(0.021)	(0.031)	(0.037)	(0.012)	(0.020)
	[0.718]	[0.976]	[0.812]	[0.981]	
	{0.994}	{0.999}	{0.994}	{0.999}	
R-squared	0.107	0.132	0.066	0.074	0.063
Number of observations	2130	2710	2124	2252	8743
Control group mean	0.038	0.102	0.032	0.019	−0.099
p-values on test of equality:					
Partial subsidy = full subsidy	0.484	0.745	0.777	0.541	0.639
1/3 subsidy = 2/3 subsidy	0.393	0.870	0.559	0.905	0.592
1/3 subsidy = full subsidy	0.762	0.847	0.571	0.483	0.809
2/3 subsidy = full subsidy	0.426	0.731	0.891	0.621	0.594

Note: Panels A, B, and C report the effects of receiving any subsidy, partial and full subsidy, and each subsidy level (1/3, 2/3, and full) on health care utilization in the short run. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. Standardized treatment effects are reported in Column 5. *p*-values for the equality of effect estimates for various pairs of treatment groups are also presented. Robust standard errors clustered at community level are reported in parentheses. Wild-cluster bootstrap *p*-values are reported in square brackets. Family-wise *p*-values are reported in curly brackets.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE 6 Effects on healthcare services utilization (long run).

	Long run				
	Visited health facility in last 4 weeks	**Visited health facility in last 6 months**	**# of visits in last 4 weeks**	**Visited facility for malaria treatment in the last 4 weeks**	**Standardized treatment effects**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Panel A					
Any subsidy	0.031**	0.080***	0.022*	0.020	0.043**
	(0.014)	(0.026)	(0.013)	(0.015)	(0.017)
	[0.054]	[0.010]	[0.141]	[0.264]	
	{0.175}	{0.083}	{0.233}	{0.306}	
R-squared	0.078	0.088	0.065	0.067	0.077
Panel B					
Partial subsidy	0.047***	0.106***	0.037***	0.034**	0.064***
	(0.013)	(0.024)	(0.012)	(0.014)	(0.015)
	[0.001]	[0.000]	[0.003]	[0.028]	
	{0.054}	{0.028}	{0.060}	{0.102}	
Full subsidy	−0.030	−0.015	−0.035	−0.036*	−0.041
	(0.019)	(0.051)	(0.022)	(0.020)	(0.030)
	[0.202]	[0.824]	[0.203]	[0.175]	
	{0.413}	{0.822}	{0.413}	{0.351}	
R-squared	0.095	0.103	0.080	0.085	0.093
Panel C					
1/3 subsidy	0.018	0.082**	0.014	0.018	0.037*
	(0.015)	(0.033)	(0.017)	(0.016)	(0.021)
	[0.329]	[0.051]	[0.511]	[0.372]	
	{0.464}	{0.167}	{0.521}	{0.464}	
2/3 subsidy	0.070***	0.124***	0.055***	0.048***	0.085***
	(0.016)	(0.032)	(0.016)	(0.018)	(0.021)
	[0.000]	[0.000]	[0.008]	[0.016]	
	{0.026}	{0.032}	{0.039}	{0.070}	
Full subsidy	−0.027	−0.012	−0.032	−0.034	−0.038
	(0.019)	(0.052)	(0.022)	(0.020)	(0.030)
	[0.277]	[0.884]	[0.228]	[0.222]	
	{0.472}	{0.867}	{0.472}	{0.398}	
R-squared	0.100	0.105	0.084	0.088	0.095
Number of observations	2228	2688	2231	2228	8912
Control group mean	0.017	0.050	0.036	0.010	−0.031
p-values on test of equality:					
Partial subsidy = full subsidy	0.0002	0.008	0.003	0.001	0.001
1/3 subsidy = 2/3 subsidy	0.012	0.319	0.092	0.155	0.118
1/3 subsidy = full subsidy	0.061	0.088	0.081	0.044	0.047
2/3 subsidy = full subsidy	0.00003	0.004	0.002	0.001	0.0003

Note: Panels A, B, and C report the effects of receiving any subsidy, partial and full subsidy, and each subsidy level (1/3, 2/3, and full) on health care utilization in the long run. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. Standardized treatment effects are reported in Column 5. *p*-values for the equality of effect estimates for various pairs of treatment groups are also presented. Robust standard errors clustered at community level are reported in parentheses. Wild-cluster bootstrap *p*-values are reported in square brackets. Family-wise *p*-values are reported in curly brackets.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE 7 *Ex-post* behavioral response (Full vs. Partial subsidy): Effects on follow-up standardized health care utilization among enrollees.

	Coefficient	Std. Error	*N*	*R*-squared
Independent variable: Full subsidy versus partial subsidy	**(1)**	**(2)**	**(3)**	**(4)**
Panel A: Behavioral responses in the short run				
Sample: Enrolled in the short run				
Short-run standardized health care utilization	−0.009	(0.011)	4723	0.009
Panel B: Behavioral responses in the long run				
Sample: Enrolled in the long run				
Short-run standardized health care utilization	−0.009	(0.020)	2505	0.007
Long-run standardized health care utilization	−0.167***	(0.054)	2656	0.046

Note: This table reports estimation results of running separate regressions of follow-up standardized health care utilization on an indicator variable that takes value of one if receiving full subsidy and zero if receiving partial subsidy. Sample is restricted to enrollees who received partial and full subsidy. Panels A and B summarize regression results when sample is restricted to those who enrolled in the short and long run, respectively. Robust standard errors clustered at community level reported in parentheses.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

In this paper, we study the long-run impacts of providing a one-time health insurance subsidy at varying levels. We find that the subsidy significantly promoted enrollment in the short run, and while the impacts were attenuated, the positive impacts remained 3 years post-intervention. We also find that the subsidy drove selective enrollment. The one-time subsidy attracted people who were ex-ante more ill and used more health care services to enroll, although this selection did not vary by subsidy level (partial vs. full). Furthermore, we observe an *ex-post* behavioral response, in which health care utilization increased in the long run for the partial subsidy group, but not for the full subsidy group.

Critics of the Ghanaian NHIS have argued that the scheme is overly generous and financially unsustainable because of the very large percentage of NHIS members under premium exemption without copayment (Alhassan et al., 2016). Our results suggest that subsidies, especially partial subsidies, could negatively affect the financial sustainability of the social health insurance program. Policy makers should be cautious of the presence of selection and behavioral responses since they are often difficult to predict and, importantly, may endanger the financial stability of an insurance program, especially one in which mandates are not enforceable.

Taken together, these findings highlight that even though short-run interventions successfully increase health insurance enrollment, their long-run success could depend on selection and behavioral responses. Our findings suggest that as health insurance continues to be introduced in developing counties, both the careful enforcement of mandatory health insurance enrollment to prevent selection and the establishment of policies that encourage desirable health behaviors need to be considered.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data available upon request.

ORCID

Armand Sim https://orcid.org/0009-0000-9659-8526

ENDNOTES

[1] Recent examples of countries that have instituted SHIs include Ghana, Kenya, Nigeria, Tanzania, and Vietnam. Countries in the process of instituting SHIs include Cambodia, Laos, Malaysia, Zimbabwe, and South Africa (Wagstaff, 2010).

[2] Wagstaff et al. (2016) and Capuno et al. (2016) find that the provision of subsidies and information does not successfully promote health insurance enrollment. Thornton et al. (2010) find that subsidies increase short-term enrollment but do not increase health care service utilization.

[3] In addition, as Dupas (2014) explains, the price level may affect the long-run adoption of health products through the anchoring mechanism, where a previously encountered price may act as an anchor and affect people's valuation of a product regardless of that product's intrinsic value.

[4] Some examples include facility delivery (Grépin et al., 2019), bed nets (Cohen & Dupas, 2010), and chlorine for water purification (Ashraf et al., 2010).

[5] Banerjee et al. (2021) study the long-run (32 months post-intervention) effects of different levels of temporary subsidies (half and full), assisted registration, and participation information in health insurance programs in urban areas in Indonesia. Baillon et al. (2022) examines the long-run (more than 3 years after intervention) effect of a one-time subsidy on health insurance enrollment in the Philippines, but the level of the subsidy does not vary.

[6] See, for example, Banerjee et al. (2004), Goldstein et al. (2013), and Das et al. (2016) for illustrations of low health care quality in developing countries. Alhassan et al. (2016) provide illustrations for Ghana.

[7] It is important to note, however, that the long-run effect of a one-time health insurance intervention is quite different from that of health product adoption, such as worm treatment and malaria bed nets. Having health insurance does not necessarily result in improved health status. To be successful, health insurance enrollment needs to promote health care service utilization and prevent moral hazard behaviors. In addition, learning about the effects of other health products, such as deworming medicine, bed nets, and water disinfectants, is less setting-specific than learning about the effects of health insurance, as its quality can vary considerably across settings.

[8] See Conti and Ginja (2023) for a comprehensive literature review on the effects of free or subsidized health insurance on utilization in developing countries.

[9] In the US context, a RAND experiment reports insignificant effects of insurance coverage on average health outcomes but finds negative effects on health outcomes for the more vulnerable subgroups (Newhouse et al., 1993). More recent studies find positive effects of exposure to public health insurance during childhood on various long-term health outcomes (Boudreaux et al., 2016; Currie et al., 2008; Miller & Wherry, 2019).

[10] There are three types of insurance schemes in Ghana: District Mutual Health Insurance Schemes (DMHIS), Private Mutual Health Insurance Schemes (PMHIS), and Private Commercial Insurance Schemes (PCHIS). The focus of this study is the DMHIS, which represents 96% of the insurance coverage in Ghana (GSS, 2009). DMHISs are operated and subsidized by the government through the National Health Insurance Fund. PMHISs are nonprofit nonsubsidized schemes run by NGOs, religious bodies and cooperative societies. PCHISs are for-profit schemes that do not receive government subsidies.

[11] The law defines an indigent as "a person who has no visible or adequate means of income or who has nobody to support him or her" and by the means test. Specifically, an indigent is a person who satisfies the following criteria: i) is unemployed and has no visible source of income, ii) does not have a fixed place of residence according to standards determined by the scheme, iii) does not live with a person who is employed and who has a fixed place of residence, and iv) does not have any identifiably consistent support from another person.

[12] CHPS are community health facilities that provide primary health care. They are located within rural communities that have limited access to larger hospitals and are staffed by nurses. Among the services offered are the treatment of common ailments (malaria and diarrheal diseases) and maternal and child care services.

[13] The exchange rate at the time of the study was \$1 = GHC 1.5.

[14] The initial intention of the original study (Asuming, 2013) was to study the short-term effects of each intervention and complementarity among interventions.

[15] The voucher could also be used to either acquire or renew insurance membership. Those who did not enroll at baseline (80%) could use the voucher at any time. Those who had already enrolled at baseline (20%) could use the voucher only if their existing renewal was due within the voucher's validity period.

[16] To facilitate the voucher redemption process, we provided the Wa West DMHIS office a list of subsidy recipients and their respective subsidy amounts. Whenever a voucher was presented, the DMHIS office validated the recipient's name and subsidy amount on the list.

[17] We decided to study long-run effects and focus only on the effects of the *Subsidy* intervention because only *Subsidy* had strong and consistent effects (see column 1 of Appendix Table B1), and the overlapping interventions in the original study made it inherently complex to disentangle the specific causal effects of each intervention.

[18] For instance, we find that complementing the subsidy with a campaign is not more effective in promoting health insurance enrollment than the combined effects of receiving the subsidy and campaign interventions separately (p-value of coefficients equality test *Subsidy Only* + *Campaign Only* = *Subsidy & Campaign* is 0.855).

[19] A similar approach is also implemented in Baillon et al. (2022).

[20] These results do not rule out the possibility of additive effects from the campaign or convenience interventions since we did not conduct any formal tests to analyze their individual contributions.

[21] We restricted the sample to communities with a population range of 30–400 residents, each located at least 1 km away from the nearest neighboring community.

[22] The household questionnaire for baseline and follow-up surveys were adapted from the Ghana Demographic and Health Survey (GDHS) 2008 and the Ghana Livings Standards Survey 2005/2006 (GLSS V).

[23] The health facility visit variable in the first follow-up survey is constructed from the following question: "The last time (in the last 4 weeks/last 6 months) (NAME) was ill or injured, did he or she visit any health facility?". In the second follow-up survey, the same variable is constructed from questions about the respondents' visits when ill. For example, an individual is said to visit a health facility in the last 6 months if his or her illness occurred in the last 6 months and, as a result, he or she sought treatment at the health facility.

[24] Self-rated health status, which is restricted to those aged 18 years or older, is available only in the follow-up surveys.

[25] In the literature, ADLs are usually constructed by asking respondents questions about their ability to perform basic daily activities, such as self-feeding, ambulation, dressing and undressing. The variables used here are derived from the following questions: "During the last 4 weeks did (NAME) have to stop his or her usual activities because of this (illness/injury)" and "For how many days (in the last month) was (NAME) unable to perform his or her usual activities."

[26] The main reasons for attrition in the first follow-up survey were as follows: deceased (17%), traveling (61%), relocated to other districts (16%), and others (6%). Information on reasons for attrition in the second follow-up survey is not available.

[27] We report additional equality tests and joint orthogonality tests in Appendix Table A4.

[28] The wealth index is obtained through a principal components analysis with dwelling characteristics (e.g., number of rooms and bedrooms in the house), enterprise (e.g., ownership of any private non-farm enterprise), livestock (e.g., number of chickens and pigs), and other assets (e.g., motorcycles and bicycles).

[29] In addition, to account for the influence of campaign and convenience interventions, we include indicators for *Subsidy + Campaign*, *Subsidy + Convenience*, and *Subsidy + Campaign + Convenience* as controls.

[30] In line with recent studies (Bessone et al., 2021; Cole & Fernando, 2021; McKenzie et al., 2022), for transparency, we reproduce our core results using the full sample while controlling for the excluded interventions—campaign-only (*Campaign*) and convenience-only (*Convenience*). Appendix Tables B5, B6, and B7 confirm that our primary conclusions remain substantially unchanged.

[31] To account for correlation within household, we also cluster standard errors at the household level. The results do not change our main conclusion (results available upon request).

[32] To do so, we stack the data for individual outcomes within each domain and run a single regression for each domain.

[33] These two methods serve different objectives. The first method is relevant for drawing general conclusions about the treatment effects on health care utilization and health status. The second method is more appropriate for examining the treatment effect of a specific outcome belonging to a set of tests.

[34] Wild cluster bootstrap p-values for all three coefficients are higher than 0.1.

[35] We calculate the arc elasticity estimates using the following formula: $\left[(Y_a - Y_b)/(Y_a + Y_b)\right] / \left[(P_a - P_b)/(P_a + P_b)\right]$, where Y and P denote enrollment rate and price, respectively. The short-run arc elasticity estimates when the price increases from \$0 to \$2.67, \$2.67 to \$5.40, and \$5.40 to \$8.13 are 0.04, 0.19, and 2.10, respectively. Comparing the arc elasticity in a zero-price setting to those in other settings could be problematic because the denominator, $(P_a - P_b)/(P_a + P_b)$ is always one if $P_b = 0$. Moreover, people tend to treat a zero price not only as a decrease in cost but also as an extra perceived benefit (Shampanier et al., 2007). These results must be interpreted with this caveat.

[36] The estimated arc elasticity is also close to the elasticity of preventive health products in developing countries, such as −0.6 for chlorine, a disinfectant that prevents water-borne diseases in Zambia (Ashraf et al., 2010), and −0.37 for insecticide-treated bed nets for malaria prevention in Kenya (Cohen & Dupas, 2010). The estimated arc elasticity is also similar to that of preventive health products in developed countries, such as −0.17 and −0.43 for preventive health care in the United States (Newhouse et al., 1993) and −0.47 for cancer screening in Korea (Kim & Lee, 2017).

[37] Framing the intervention as a subsidy (often perceived positively) rather than a price (usually perceived negatively) could lead to different responses from individuals. When the offer is framed as a subsidy, respondents perceived it as a benefit or a gain, resulting in a larger enrollment increase when the subsidy is introduced (from zero to one-third) than when it increases from one-third to full (which would make the price zero).

[38] This approach requires an assumption that always-takers in the partial and in the full subsidy groups are identical, which is reasonable in that always-takers are those who enroll in health insurance regardless of financial subsidies.

[39] The estimated share of compliers, always-takers, and never-takers are 47.4%, 27.1%, and 25.5% in the short run, and 24.3%, 23.0% and 52.7% in the long run; for control versus partial subsidy 44.2%, 27.1%, and 28.6% in the short run and 20.9%, 23%, and 56% in the long run; for control versus full subsidy 50.2%, 27.1%, and 22.6% in the short run and 27%, 23%, and 49.9% in the long run.

[40] We present the results on the components of standardized variables and other variables in Appendix Table A7 (control vs. any subsidy), Table A8 (control vs. partial subsidy), and Table A9 (control vs. full subsidy).

[41] We are not able to compare the partial and full subsidy groups using this approach because the differences in health insurance take-up rates are too small to calculate complier characteristics.

[42] We present the results on the components of standardized variables in Appendix Tables A10 and A11.

[43] Learning might be especially true for those who pay insurance premiums (or those who enrolled in response to a partial subsidy) because people who must pay higher costs tend to reduce information asymmetry associated with health care providers (Gaynor, 1994; McGuire, 2000). Indeed, studies have documented experimental evidence that poor people who received subsidies for health or other types of insurance may have initial low uptake because they first seek to understand the value of the insurance programs (Banerjee et al., 2004; Cole et al., 2013; Domurat et al., 2021).

[44] There are two possible mechanisms for the lack of long-run health outcomes: moral hazard and a change in subjective perception regarding health status. We first investigate the health behaviors of individuals who are 12 years old or older regarding the use of bed nets and safe water technologies (Appendix Table A15). We find some suggestive evidence on the decrease in the overall health investments in the full subsidy group, which is not consistent with the results in health utilization and status. This finding rules out moral hazard as a plausible channel. Second, such a decrease can happen when people have frequent contact with health facilities, learn about the specific symptoms of illnesses, and change their perception regarding their own subjective health status (Dow et al., 1997; Finkelstein et al., 2012). Additionally, those who receive a diagnosis could have a greater awareness of the times or periods that they were sick. As a result, they are more likely to report being ill. Unfortunately, we are unable to test these conjectures in our data. More research is needed to verify any further precise mechanisms through which health insurance enrollment and health care utilization can result in a decline in self-reported health status.

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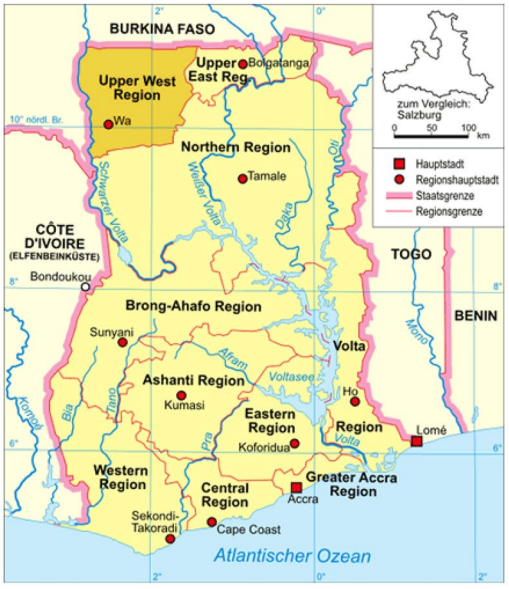
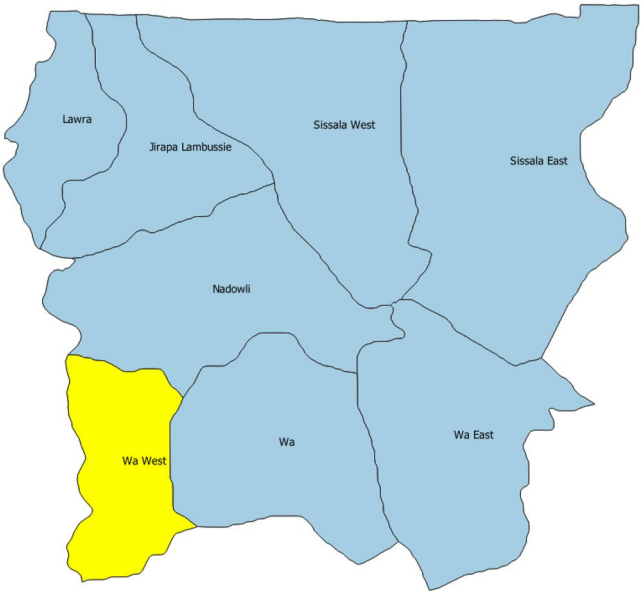
APPENDIX A



(a)



(b)

FIGURE A1 Map. (a) Map of Ghana. (b) Map of Upper West Region. This map shows Ghana (upper panel) and the Upper West region of Ghana (lower panel), which includes Wa West district (highlighted). [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE A1 National Health Insurance Scheme (NHIS) coverage.

Included services	Exclusion list
1. Out-patient services i) General and specialized consultation and review ii) Requested investigation (including laboratory investigations, x-rays and ultrasound scanning) iii) Medication (prescription drugs on the NHIS drug list) iv) HIV/AIDS symptomatic treatment for opportunistic infection v) Out-patient/Day surgery operations including hernia repairs, incision and drainage, hemorrhoidectomy vi) Out-patient physiotherapy 2. In-patient services i) General and specialist in-patient care ii) Requested investigations iii) Medication (prescription drugs on NHIS drug list) iv) Cervical and breast cancer treatment v) Surgical operations vi) In-patient physiotherapy vii) Accommodation in general ward viii) Feeding (where available) 3. Oral health services i) Pain relief which includes incision and drainage, tooth extraction and temporary relief ii) Dental restoration which includes simple amalgam fillings and temporary dressing 4. Eye care services i) Refraction, visual fields and A-Scan ii) Keratometry iii) Cataract removal iv) Eye lid surgery 5. Maternity care i) Antenatal care ii) Deliveries (normal and assisted) iii) Caesarian section iv) Postnatal care 6. Emergencies i) Medical emergencies ii) Surgical emergencies including brain surgery due to accidents iii) Pediatric emergencies iv) Obstetric and gynecological emergencies v) Road traffic accidents vi) Industrial and workplace accidents vii) Dialysis for acute renal failure	1. Rehabilitation other than physiotherapy 2. Appliances and protheses including optical aids, hearing aids, othopedic aids and dentures 3. Cosmetic surgeries and esthetic treatment 4. HIV retroviral drugs 5. Assisted reproduction for example, artificial insemination and gynecological hormone replacement therapy 6. Echocardiography 7. Photography 8. Angiography 9. Orthotics 10. Dialysis for chronic renal failure 11. Heart and brain surgery other than hose resulting from accident 12. Cancer treatment other than cervical ad breast cancer 13. Organ transplating 14. All drugs that not listed on the NHIS drug list 15. Diagnosis and treatment abroad 16. Medical examinations for purposes of visa applications, education and institutional driving license 17. VIP ward accommodation 18. Mortuary services

Source: NHIA (2011).

TABLE A2 Attrition.

	Attrited	
	Short-run	**Long-run**
	(1)	**(2)**
Panel A		
Any subsidy	0.006	−0.047
	(0.024)	(0.036)
	[0.819]	[0.224]
R-squared	0.144	0.104

(Continues)

TABLE A2 (Continued)

	Attrited	
	Short-run	Long-run
	(1)	(2)
Panel B		
Partial subsidy	0.004	−0.042
	(0.025)	(0.038)
	[0.896]	[0.302]
Full subsidy	0.013	−0.065
	(0.044)	(0.053)
	[0.810]	[0.311]
R-squared	0.144	0.104
Panel C		
1/3 subsidy	−0.005	−0.039
	(0.043)	(0.051)
	[0.925]	[0.534]
2/3 subsidy	0.011	−0.045
	(0.024)	(0.042)
	[0.665]	[0.314]
Full subsidy	0.014	−0.066
	(0.044)	(0.051)
	[0.780]	[0.298]
R-squared	0.144	0.104
Mean	0.05	0.21
Number of observations	2953	2953

Note: Dependent variable is a binary variable indicating whether an individual had been attrited in the short- and long-run follow-up surveys. All regressions include a standard set of covariates (individual, household, and community). Robust standard errors clustered at community level reported in parentheses.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE A3 Differential attrition analysis.

	Short run			Long run		
	Partial versus control	Full versus control	Full versus partial	Partial versus control	Full versus control	Full versus partial
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Control variables						
Age (years)	−8.459	−3.536	4.923	−3.597	−0.249	3.348
Male	−0.204**	−0.354***	−0.149*	−0.086	−0.048	0.038
Christian	−0.627***	−0.186	0.441*	−0.191*	−0.013	0.177
Dagaaba ethnic group	−0.431	−0.259	0.171	−0.078	0.053	0.131
Has some formal education	−0.079	−0.172	−0.093	0.042	−0.069	−0.111
Household size	3.452***	0.005	−3.447**	0.666	−0.765	−1.431*
Household assets (principal component score)	−0.602	−1.265*	−0.663	−0.342	−0.165	0.177
Distance to district insurance office (km)	−8.587**	2.236	10.823**	−1.212	6.165*	7.377**
Distance to nearest health facility (km)	1.580	−0.117	−1.697	0.389	−0.086	−0.475
Ever enrolled in NHIS	−0.008	−0.060	−0.052	−0.056	−0.073	−0.017

TABLE A3 (Continued)

	Short run			Long run		
	Partial versus control	Full versus control	Full versus partial	Partial versus control	Full versus control	Full versus partial
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Baseline values of outcome variables						
Enrollment	0.130	0.122	−0.008	0.058	0.089	0.031
Ill in the last 4 weeks	−0.021	−0.008	0.013	0.036	0.026	−0.010
Number of sick days in the last 4 weeks	−0.482	0.684	1.166	0.340	0.577	0.237
Could not do normal activities in the last 4 weeks	−0.012	0.035	0.046	0.040	0.050	0.010
No. of days could not perform normal activities in the last 4 weeks	−0.313	−0.156	0.157	0.559**	0.365	−0.194
Visited health facility in the last 4 weeks	0.074	0.001	−0.072	0.028	−0.003	−0.031
Visited health facility in the last 6 months	−0.156**	−0.211***	−0.055	0.007	−0.035	−0.042
Number of health facility visit in the last 4 weeks	0.039	−0.161	−0.199	0.034	−0.044	−0.079
Visited health facility for malaria treatment in the last 4 weeks	−0.061	−0.057	0.003	−0.022	−0.025*	−0.003
Made out of pocket expense in the last 6 month	−0.049	−0.091	−0.042	0.023	−0.016	−0.039

Note: This table presents regression coefficients of interaction terms of indicator of attrition and treatment status in the short run (columns 1–3) and in the long run (columns 4–6). Dependent variable is baseline characteristics in Panels A and B. Coefficients of attrition and treatment status are not shown. Standard errors are clustered at the community level.

TABLE A4 Additional balance tests.

	Mean					*N*	*p*-values of difference
	All	Control	One-third	Two-thirds	Full		One-third = two-thirds = full = control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Control variables							
Age (years)	23.780	24.313	25.494	23.538	22.694	2954	0.390
Male	0.481	0.475	0.484	0.466	0.497	2954	0.578
Christian	0.417	0.373	0.446	0.475	0.431	2954	0.801
Dagaaba ethnic group	0.517	0.458	0.611	0.667	0.476	2954	0.370
Has some formal education	0.335	0.337	0.315	0.322	0.346	2954	0.976
Household size	8.703	8.454	8.268	8.506	9.267	2953	0.517
Household assets (principal component score)	0.601	0.266	0.846	0.535	0.971	2953	0.061
Distance to district insurance office (km)	20.010	20.37	24.717	23.817	15.904	2954	0.303
Distance to nearest health facility (km)	5.394	5.166	5.388	4.48	6.184	2954	0.149
Ever enrolled in NHIS	0.358	0.302	0.481	0.385	0.373	2954	0.090
Panel B: Baseline values of outcome variables							
Enrollment	0.198	0.197	0.236	0.238	0.166	2954	0.690
Ill in the last 4 weeks	0.123	0.105	0.143	0.153	0.121	2954	0.532
Number of sick days in the last 4 weeks	0.918	0.846	1.350	1.054	0.790	2927	0.565
Could not do normal activities in the last 4 weeks	0.076	0.060	0.071	0.099	0.084	2919	0.428

(Continues)

TABLE A4 (Continued)

	Mean					N	p-values of difference
	All	Control	One-third	Two-thirds	Full		One-third = two-thirds = full = control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of days could not perform normal activities in the last 4 weeks	0.544	0.480	0.614	0.619	0.559	2815	0.867
Visited health facility in the last 4 weeks	0.039	0.036	0.069	0.059	0.021	2435	0.301
Visited health facility in the last 6 months	0.074	0.074	0.099	0.082	0.060	2954	0.639
Number of health facility visit in the last 4 weeks	0.066	0.063	0.125	0.105	0.027	2443	0.117
Visited health facility for malaria treatment in the last 4 weeks	0.010	0.011	0.007	0.013	0.007	2435	0.925
Made out of pocket expense in the last 6 months	0.136	0.133	0.124	0.192	0.112	2954	0.306
p-values of joint orthogonality test							
Control variables							0.425
Outcomes							0.991

Note: Columns 1–5 report mean of baseline characteristics of all respondents, control group, and treatment groups. Column 6 reports total number of observations. Column 7 reports the *p*-value from balance tests for each characteristic. In the last two rows we report a joint test of orthogonality for sets of outcomes and covariates separately. To perform the joint test of orthogonality we regress the treatment variable that takes on all covariates and we then test the joint null hypothesis that all covariates have a zero coefficient. We estimate a categorical logit model because the treatment variable has more than one value.

TABLE A5 Breakdown of enrollment rate in each round.

Baseline			Short run			Long run		
	N	%		N	%		N	%
Enrolled	586	19.84	Enrolled	394	67.24	Enrolled	172	43.65
						Not enrolled	165	41.88
						Missing	57	14.47
			Not enrolled	141	24.06	Enrolled	33	23.40
						Not enrolled	81	57.45
			Missing	51	8.70	Missing	27	19.15
Not enrolled	2368	80.16	Enrolled	1153	48.69	Enrolled	470	40.76
						Not enrolled	482	41.80
						Missing	201	17.43
			Not enrolled	1097	46.33	Enrolled	190	17.32
						Not enrolled	664	60.53
			Missing	118	4.98	Missing	243	22.15
			Enrolled in short run	1547	55.55	Enrolled	642	41.50
						Not enrolled	647	41.82
						Missing	258	16.68
			Not enrolled in short run	1238	44.45	Enrolled	223	18.01
						Not enrolled	745	60.18
						Missing	270	21.81

Note: This table reports the number of people and proportion of enrollment rate in each round. The number of missing observations on enrollment status between rounds are either caused by attrition or missing enrollment information from the non-attrited respondents.

TABLE A6 Selective retention and new enrollment by health status and health care utilization.

	Coefficient	Standard error	*N*	*R*-squared
	(1)	(2)	(3)	(4)
Panel A: Selective retention				
Panel A1				
Sample: Enrolled in the baseline				
Independent variable: Enrolled in the first follow-up				
Standardized health status (baseline)	0.030*	(0.015)	3112	0.004
Standardized health care utilization (baseline)	0.055*	(0.031)	1842	0.004
Panel A2				
Sample: Enrolled in the baseline				
Independent variable: Enrolled in the second follow-up				
Standardized health status (baseline)	0.044*	(0.024)	2629	0.010
Standardized health care utilization (baseline)	0.065	(0.050)	1557	0.008
Panel A3				
Sample: Enrolled in the first follow-up				
Independent variable: Enrolled in the second follow-up				
Standardized health status (first follow-up)	0.021***	(0.006)	8115	0.006
Standardized health care utilization (first follow-up)	0.045***	(0.013)	4887	0.006
Panel B: Selective new enrollment				
Panel B1				
Sample: Not enrolled in the baseline				
Independent variable: Enrolled in the first follow-up				
Standardized health status (baseline)	−0.002	(0.007)	13,226	0.0001
Standardized health care utilization (baseline)	−0.004	(0.009)	7864	0.0001
Panel B2				
Sample: Not enrolled in the baseline				
Independent variable: Enrolled in the second follow-up				
Standardized health status (baseline)	0.013	(0.008)	10,621	0.002
Standardized health care utilization (baseline)	0.024*	(0.014)	6304	0.004
Panel B3				
Sample: Not enrolled in the baseline				
Independent variable: Enrolled in the second follow-up				
Standardized health status (first follow-up)	0.004	(0.009)	6122	0.0001
Standardized health care utilization (first follow-up)	0.058***	(0.021)	3659	0.013

Note: This table reports estimation results of running univariate regression of each standardized health characteristics on an enrollment indicator in short and long-run. Panel A examines selective retention. Samples in Panels A1 and A2 are restricted to those who enrolled in the baseline, while Panel A3 restricted to those enrolled in the short run. Panel B examines selective new enrollment. Samples in Panels B1 and B2 are restricted to those who did not enroll in the baseline, while Panel B3 restricted to those who did not enroll in the short run. Robust standard errors clustered at community level reported in parentheses.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE A7 Additional results of selection by Subsidy (No Subsidy vs. Subsidy): Characteristics of compliers, always-takers, and never-takers.

	Short run						Long run					
	Mean			*t*-stat			Mean			*t*-stat		
	Complier	Always	Never	C = A	C = N	A = N	Complier	Always	Never	C = A	C = N	A = N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Health status and health care utilization												
Health status												
Illness												
Number of sick days in the last 4 weeks	1.03	0.75	0.89	1.62	0.91	−0.58	0.78	1.05	0.93	−1.03	−1.06	0.41
Could not do normal activities in the last 4 weeks	0.10	0.04	0.08	5.80	1.93	−2.28	0.10	0.10	0.07	0.18	2.97	1.07
No. of days could not perform normal activities in the last 4 weeks	0.74	0.33	0.43	3.39	3.96	−0.69	0.42	0.68	0.54	−1.21	−1.20	0.61
Illness due to Malaria												
Number of sick days in the last 4 weeks	0.29	0.32	0.16	−0.30	3.12	1.63	0.33	0.53	0.14	−1.08	3.83	2.03
Could not do normal activities in the last 4 weeks	0.04	0.02	0.02	3.23	2.16	−0.71	0.07	0.03	0.01	3.47	13.59	1.26
No. of days could not perform normal activities in the last 4 weeks	0.17	0.16	0.13	0.16	1.05	0.40	0.29	0.32	0.05	−0.16	12.68	1.50
Health care utilization												
Visited health facility in the last 4 weeks	0.04	0.05	0.03	−0.43	1.52	1.14	0.04	0.06	0.03	−1.26	1.83	1.79
Visited health facility in the last 6 months	0.07	0.09	0.06	−1.16	0.73	1.37	0.05	0.13	0.05	−3.32	−0.04	3.11
Number of visits in the last 4 weeks	0.06	0.08	0.05	−0.80	0.81	1.07	0.02	0.10	0.06	−2.21	−2.57	1.03
Visited health facility in the last 4 weeks for malaria treatment	0.01	0.01	0.01	0.43	1.73	0.50	0.01	0.03	0.00	−1.15	8.20	2.12
Panel B: Other characteristics												
Age	24.34	20.48	24.39	3.61	−0.05	−2.58	19.11	21.29	27.02	−1.53	−9.72	−3.50
Male	0.51	0.47	0.48	1.18	1.17	−0.15	0.50	0.44	0.51	1.59	−0.64	−1.70
Christian	0.43	0.51	0.40	−2.74	1.24	2.90	0.4	0.5	0.4	−4.91	−3.12	2.92
Dagaaba (ethnic group)	0.61	0.54	0.44	2.14	6.89	2.79	0.59	0.53	0.51	1.62	4.14	0.48
Has some formal education	0.38	0.35	0.26	0.81	5.61	2.78	0.43	0.35	0.30	2.30	7.89	1.47
Household size	9.35	8.34	8.57	5.11	5.41	−0.92	10.18	7.99	8.87	12.52	11.25	−4.03

TABLE A7 (Continued)

	Short run						Long run					
	Mean			*t*-stat			Mean			*t*-stat		
	Complier	Always	Never	C = A	C = N	A = N	Complier	Always	Never	C = A	C = N	A = N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Household assets (principal component score)	1.09	0.77	0.59	2.56	5.69	1.19	2.30	0.17	0.61	21.36	36.13	−3.59
Ever enrolled in NHIS	0.30	0.65	0.30	−12.98	0.23	10.02	0.40	0.41	0.41	−0.24	−0.51	−0.02
Currently enrolled in NHIS	0.05	0.47	0.15	−14.99	−6.38	9.39	0.13	0.30	0.17	−5.22	−2.61	3.77

Note: This table presents the mean characteristics of compliers, always-takers, and never-takers comparing control group with any subsidy group, which are estimated from Equation (3). Panel A presents statistics on the component variables of standardized health status and health care utilization. Panel B presents statistics on the other socio-economic characteristics. Columns 4–6 and 10–12 present the *t*-statistics from the two-sample *t*-test comparing compliers with always-takers, compliers with never-takers, and always-takers with never-takers, respectively.

TABLE A8 Additional Results of Selection by Subsidy (No Subsidy vs. Partial Subsidy): Characteristics of Compliers, Always-takers, and Never-takers.

	Short run						Long run					
	Mean			*t*-stat			Mean			*t*-stat		
	Complier	Always	Never	C = A	C = N	A = N	Complier	Always	Never	C = A	C = N	A = N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Health status and health care utilization												
Health status												
Illness												
Number of sick days in the last 4 weeks	1.34	0.75	1.15	3.43	0.68	−1.28	1.18	1.05	1.08	0.47	0.43	−0.07
Could not do normal activities in the last 4 weeks	0.10	0.04	0.09	5.67	0.58	−2.30	0.11	0.10	0.07	0.89	3.36	1.08
No. of days could not perform normal activities in the last 4 weeks	0.71	0.33	0.55	3.13	1.33	−1.22	0.32	0.68	0.49	−1.64	−1.31	0.74
Illness due to Malaria												
Number of sick days in the last 4 weeks	0.43	0.32	0.17	1.29	4.41	1.36	0.51	0.53	0.20	−0.14	3.20	1.59
Could not do normal activities in the last 4 weeks	0.04	0.02	0.03	3.47	1.30	−0.82	0.07	0.03	0.02	3.52	8.17	0.93
No. of days could not perform normal activities in the last 4 weeks	0.14	0.16	0.14	−0.22	0.12	0.25	0.23	0.32	0.06	−0.51	5.89	1.44
Health care utilization												
Visited health facility in the last 4 weeks	0.08	0.05	0.04	2.13	2.38	0.15	0.07	0.06	0.05	0.51	1.95	0.64
Visited health facility in the last 6 months	0.09	0.09	0.07	0.15	1.00	0.62	0.08	0.13	0.06	−2.41	1.15	2.65
Number of visits in the last 4 weeks	0.13	0.08	0.07	1.62	2.39	0.27	0.05	0.10	0.11	−1.28	−1.70	−0.08

(Continues)

TABLE A8 (Continued)

	Short run						Long run					
	Mean			*t*-stat			Mean			*t*-stat		
	Complier	Always	Never	C = A	C = N	A = N	Complier	Always	Never	C = A	C = N	A = N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Visited health facility in the last 4 weeks for malaria treatment	0.01	0.01	0.01	0.73	0.65	−0.04	0.02	0.03	0.00	−0.55	6.09	1.96
Panel B: Other characteristics												
Age	26.20	20.48	25.19	5.38	0.66	−2.50	26.07	21.29	26.39	3.39	−0.26	−2.73
Male	0.50	0.47	0.44	0.83	1.68	0.73	0.48	0.44	0.50	1.19	−0.64	−1.33
Christian	0.47	0.51	0.44	−1.41	0.97	1.66	0.49	0.54	0.43	−1.27	2.24	2.35
Dagaaba (ethnic group)	0.79	0.54	0.50	8.72	8.73	0.96	0.80	0.53	0.62	8.01	7.80	−1.93
Has some formal education	0.34	0.35	0.26	−0.33	2.79	2.26	0.36	0.35	0.29	0.16	2.72	1.45
Household size	8.50	8.34	8.16	0.78	1.86	0.69	8.23	7.99	8.68	1.32	−2.80	−2.85
Household assets (principal component score)	0.81	0.77	0.41	0.32	3.64	2.16	2.08	0.17	0.51	22.86	23.47	−2.39
Ever enrolled in NHIS	0.36	0.65	0.29	−10.82	2.25	8.71	0.50	0.41	0.41	2.67	3.43	−0.08
Currently enrolled in NHIS	0.16	0.47	0.10	−10.98	3.06	10.43	0.26	0.30	0.19	−1.44	2.97	2.82

Note: This table presents the mean characteristics of compliers, always-takers, and never-takers comparing control group with partial subsidy group, which are estimated from Equation (3). Panel A presents statistics on the component variables of standardized health status and health care utilization. Panel B presents statistics on the other socio-economic characteristics. Columns 4–6 and 10–12 present the *t*-statistics from the two-sample *t*-test comparing compliers with always-takers, compliers with never-takers, and always-takers with never-takers, respectively.

TABLE A9 Additional Results of Selection by Subsidy (No Subsidy vs. Full Subsidy): Characteristics of Compliers, Always-takers, and Never-takers.

	Short run						Long run					
	Mean			*t*-stat			Mean			*t*-stat		
	Complier	Always	Never	C = A	C = N	A = N	Complier	Always	Never	C = A	C = N	A = N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Health status and health care utilization												
Health status												
Illness												
Number of sick days in the last 4 weeks	0.79	0.75	0.59	0.21	1.37	0.73	0.52	1.05	0.79	−2.00	−1.60	0.84
Could not do normal activities in the last 4 weeks	0.11	0.04	0.07	5.93	2.30	−1.24	0.09	0.10	0.07	−0.28	1.23	0.90
No. of days could not perform normal activities in the last 4 weeks	0.77	0.33	0.31	3.59	5.09	0.17	0.48	0.68	0.58	−0.94	−0.66	0.41

TABLE A9 (Continued)

	Short run						Long run					
	Mean			*t*-stat			Mean			*t*-stat		
	Complier	Always	Never	C = A	C = N	A = N	Complier	Always	Never	C = A	C = N	A = N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Illness due to Malaria												
Number of sick days in the last 4 weeks	0.18	0.32	0.14	−1.54	0.67	1.64	0.22	0.53	0.09	−1.69	4.13	2.36
Could not do normal activities in the last 4 weeks	0.04	0.02	0.02	3.04	1.87	−0.29	0.07	0.03	0.01	3.46	11.66	1.46
No. of days could not perform normal activities in the last 4 weeks	0.19	0.16	0.12	0.46	1.21	0.48	0.33	0.32	0.04	0.06	11.63	1.54
Health care utilization												
Visited health facility in the last 4 weeks	0.01	0.05	0.01	−2.45	0.80	2.56	0.02	0.06	0.01	−2.38	3.06	2.99
Visited health facility in the last 6 months	0.05	0.09	0.05	−2.19	0.38	1.87	0.04	0.13	0.05	−3.92	−0.72	3.25
Number of visits in the last 4 weeks	0.00	0.08	0.01	−2.72	−1.54	2.20	0.00	0.10	0.01	−2.81	−2.36	2.33
Visited health facility in the last 4 weeks for malaria treatment	0.01	0.01	0.00	0.20	N/A	1.42	0.01	0.03	0.00	−1.53	N/A	2.26
Panel B: Other characteristics												
Age	22.88	20.48	23.49	2.24	−0.42	−1.66	14.60	21.29	27.62	−4.75	−12.06	−3.53
Male	0.51	0.47	0.52	1.47	−0.17	−1.05	0.51	0.44	0.52	1.85	−0.43	−1.74
Christian	0.40	0.51	0.36	−3.78	1.17	3.33	0.28	0.54	0.41	−7.39	−5.20	2.95
Dagaaba (ethnic group)	0.46	0.54	0.37	−2.91	2.67	3.91	0.45	0.53	0.41	−2.32	1.43	2.71
Has some formal education	0.40	0.35	0.25	1.71	4.89	2.50	0.48	0.35	0.30	3.70	7.46	1.24
Household size	10.02	8.34	9.04	8.58	4.41	−2.30	11.44	7.99	9.05	22.92	15.08	−4.09
Household assets (principal component score)	1.30	0.77	0.79	4.33	3.73	−0.10	2.44	0.17	0.71	26.43	38.76	−4.06
Ever enrolled in NHIS	0.26	0.65	0.30	−14.91	−1.41	8.23	0.33	0.41	0.41	−2.12	−2.85	0.04
Currently enrolled in NHIS	−0.04	0.47	0.21	−18.58	−9.02	6.35	0.06	0.30	0.15	−7.80	−5.38	4.19

Note: This table presents the mean characteristics of compliers, always-takers, and never-takers comparing control group with full subsidy group, which are estimated from Equation (3). Panel A presents statistics on the component variables of standardized health status and health care utilization. Panel B presents statistics on the other socio-economic characteristics. Columns 4–6 and 10–12 present the *t*-statistics from the two-sample *t*-test comparing compliers with always-takers, compliers with never-takers, and always-takers with never-takers, respectively.

TABLE A10 Results of Selection by Subsidy Level (Partial vs. Full): Baseline Health Characteristics.

	Baseline health status						Baseline health care utilization			
	# Days ill last month	Could not perform normal daily activities due to illness last month	# days could not perform normal daily activities in the last month	# Days ill last month due to malaria	Could not perform normal daily activities due to illness last month due to malaria	# days could not perform normal daily activities in the last month due to malaria	Visited health facility in last 4 weeks	Visited health facility in last 6 months	# of visits in last 4 weeks	Visited facility for malaria treatment in the last 4 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A										
Sample: Enrolled in the short run										
Full subsidy	−0.196	0.026	0.288	0.004	0.018	0.135	−0.037	−0.014	−0.093*	0.010
	(0.494)	(0.030)	(0.342)	(0.242)	(0.020)	(0.187)	(0.032)	(0.031)	(0.051)	(0.014)
N	1238	1233	1186	1238	1233	1186	1090	1244	1091	1090
R-squared	0.004	0.006	0.005	0.009	0.013	0.005	0.023	0.008	0.018	0.012
Panel B										
Sample: Enrolled in the long run										
Full subsidy	−0.097	0.022	0.315	0.154	0.040	0.262	0.013	0.020	0.025	0.021
	(0.437)	(0.042)	(0.393)	(0.410)	(0.042)	(0.384)	(0.042)	(0.038)	(0.051)	(0.026)
N	661	657	625	661	657	625	572	664	573	572
R-squared	0.010	0.015	0.009	0.018	0.025	0.011	0.033	0.020	0.033	0.027
Panel C										
Sample: Enrolled in the short and long run										
Full subsidy	0.940	0.089	1.024	0.775	0.080	0.776	−0.053	0.015	−0.046	0.003
	(0.652)	(0.061)	(0.642)	(0.651)	(0.063)	(0.640)	(0.048)	(0.048)	(0.048)	(0.021)
N	422	421	408	422	421	408	375	424	375	375
R-squared	0.038	0.033	0.049	0.056	0.053	0.057	0.057	0.016	0.052	0.008
Panel D										
Sample: Enrolled in all rounds										
Full subsidy	−1.043	−0.018	0.202	−0.336	0.057	0.335	0.105	0.070	0.063	0.072
	(0.846)	(0.105)	(0.446)	(0.528)	(0.058)	(0.282)	(0.079)	(0.086)	(0.102)	(0.056)
N	127	126	117	127	126	117	108	127	109	108
R-squared	0.032	0.037	0.006	0.025	0.049	0.018	0.114	0.065	0.141	0.076

Note: This table presents selection by subsidy level based on the component variables of standardized health care utilization in short and long run.

TABLE A11 Results of Selection by Subsidy Level (Partial vs. Full): Short and Long-run Health Care Utilization.

	Short-run health care utilization				Long-run health care utilization			
	Visited health facility in last 4 weeks	Visited health facility in last 6 months	# of visits in last 4 weeks	Visited facility for malaria treatment in the last 4 weeks	Visited health facility in last 4 weeks	Visited health facility in last 6 months	# of visits in last 4 weeks	Visited facility for malaria treatment in the last 4 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Sample: Enrolled in the short run								
Full subsidy	−0.010	−0.001	0.004	−0.018				
	(0.017)	(0.027)	(0.012)	(0.011)				
N	1152	1223	1148	1200				
R-squared	0.017	0.025	0.010	0.008				
Panel B								
Sample: Enrolled in the long run								
Full subsidy	0.005	−0.022	0.030	−0.032**	−0.122***	−0.245***	−0.101**	−0.091**
	(0.033)	(0.032)	(0.043)	(0.012)	(0.035)	(0.076)	(0.041)	(0.037)
N	611	651	608	635	664	664	664	664
R-squared	0.009	0.022	0.009	0.008	0.045	0.091	0.034	0.035
Panel C								
Sample: Enrolled in the short and long run								
Full subsidy	−0.015	0.053	0.014	−0.010	−0.102**	−0.197***	−0.074*	−0.081**
	(0.029)	(0.054)	(0.044)	(0.025)	(0.037)	(0.052)	(0.039)	(0.037)
N	393	420	392	409	424	424	424	424
R-squared	0.007	0.011	0.009	0.002	0.035	0.097	0.024	0.033
Panel D								
Sample: Enrolled in all rounds								
Full subsidy	−0.001	−0.064	−0.011	−0.068*	−0.170***	−0.133	−0.087	−0.093
	(0.035)	(0.096)	(0.033)	(0.037)	(0.055)	(0.108)	(0.076)	(0.055)
N	120	124	119	124	127	127	127	127
R-squared	0.059	0.154	0.096	0.051	0.071	0.074	0.029	0.042

Note: This table presents selection by subsidy level based on the component variables of standardized health care utilization in short and long run.

TABLE A12 Effects of subsidy (level) on out-of-pocket (OOP) health care expenses.

	Made out-of-pocket for health services in the last 6 months	
	Short-run	Long-run
	(1)	(2)
Panel A		
Any subsidy	−0.009	0.002
	(0.016)	(0.007)
	[0.606]	[0.767]
R-squared	0.094	0.090
Panel B		
Partial subsidy	−0.009	0.013
	(0.015)	(0.009)
	[0.620]	[0.239]

(Continues)

TABLE A12 (Continued)

	Made out-of-pocket for health services in the last 6 months	
	Short-run	Long-run
	(1)	(2)
Full subsidy	−0.012	−0.037*
	(0.023)	(0.022)
	[0.606]	[0.063]
R-squared	0.094	0.103
Panel C		
1/3 subsidy	−0.014	0.026
	(0.014)	(0.027)
	[0.362]	[0.687]
2/3 subsidy	−0.004	0.004
	(0.020)	(0.012)
	[0.845]	[0.792]
Full subsidy	−0.011	−0.039
	(0.023)	(0.024)
	[0.676]	[0.102]
R-squared	0.094	0.105
Number of observations	2805	2688
Control group mean	0.046	0.013
p-values on test of equality:		
Partial subsidy = full subsidy	0.827	0.086
1/3 subsidy = 2/3 subsidy	0.550	0.533
1/3 subsidy = full subsidy	0.838	0.196
2/3 subsidy = full subsidy	0.721	0.020

Note: All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. *p*-values for the equality of effect estimates for various pairs of treatment groups are also presented. Robust standard errors clustered at community level are reported in parentheses. Wild-cluster bootstrap *p*-values are reported in square brackets.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE A13 Effects on health status (short run).

	Short run				
	Feeling unhealthy	# of days ill last 4 weeks	Could not perform normal daily activities due to illness last 4 weeks	# of days could not perform normal daily activities due to illness in the last 4 weeks	Standardized treatment effects
	(1)	(2)	(3)	(4)	(5)
Panel A					
Any subsidy	−0.126***	−0.337**	−0.014	−0.170	−0.029**
	(0.037)	(0.142)	(0.019)	(0.392)	(0.014)
	[0.003]	[0.035]	[0.535]	[0.696]	
	{0.035}	{0.134}	{0.677}	{0.723}	
R-squared	0.192	0.086	0.080	0.093	0.063
Panel B					
Partial subsidy	−0.129***	−0.316**	−0.013	−0.081	−0.026*
	(0.037)	(0.135)	(0.018)	(0.370)	(0.013)

TABLE A13 (Continued)

	Short run				
	Feeling unhealthy	**# of days ill last 4 weeks**	**Could not perform normal daily activities due to illness last 4 weeks**	**# of days could not perform normal daily activities due to illness in the last 4 weeks**	**Standardized treatment effects**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	[0.003]	[0.039]	[0.558]	[0.858]	
	{0.035}	{0.136}	{0.704}	{0.862}	
Full subsidy	−0.117**	−0.417*	−0.021	−0.516	−0.042*
	(0.044)	(0.210)	(0.030)	(0.512)	(0.022)
	[0.010]	[0.079]	[0.525]	[0.360]	
	{0.106}	{0.212}	{0.540}	{0.489}	
R-squared	0.192	0.086	0.080	0.094	0.064
Panel C					
1/3 subsidy	−0.118***	−0.412**	−0.012	−0.392	−0.035*
	(0.042)	(0.166)	(0.024)	(0.418)	(0.018)
	[0.011]	[0.036]	[0.667]	[0.406]	
	{0.081}	{0.100}	{0.669}	{0.544}	
2/3 subsidy	−0.137***	−0.244	−0.013	0.165	−0.018
	(0.044)	(0.171)	(0.020)	(0.428)	(0.015)
	[0.011]	[0.235]	[0.620]	[0.775]	
	{0.088}	{0.520}	{0.735}	{0.759}	
Full subsidy	−0.119***	−0.402*	−0.021	−0.458	−0.040*
	(0.044)	(0.213)	(0.030)	(0.511)	(0.022)
	[0.009]	[0.111]	[0.534]	[0.424]	
	{0.105}	{0.248}	{0.554}	{0.554}	
R-squared	0.193	0.087	0.080	0.095	0.064
Number of observations	861	2768	2775	2677	8824
Control group mean	0.817	0.617	0.081	1.379	−0.019
p-values on test of equality:					
Partial subsidy = full subsidy	0.737	0.473	0.712	0.180	0.287
1/3 subsidy = 2/3 subsidy	0.685	0.395	0.942	0.208	0.392
1/3 subsidy = full subsidy	0.984	0.954	0.713	0.858	0.755
2/3 subsidy = full subsidy	0.662	0.331	0.761	0.102	0.229

Note: Panels A, B, and C report the effects of receiving any subsidy, partial and full subsidy, and each subsidy level (1/3, 2/3, and full) on health status in the short run. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. Standardized treatment effects are reported in Column 5. *p*-values for the equality of effect estimates for various pairs of treatment groups are also presented. Robust standard errors clustered at community level are reported in parentheses. Wild-cluster bootstrap *p*-values are reported in square brackets. Family-wise *p*-values are reported in curly brackets.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE A14 Effects on health status (long run).

	Long run				
	Feeling unhealthy	**# of days ill last 4 weeks**	**Could not perform normal daily activities due to illness last 4 weeks**	**# of days could not perform normal daily activities due to illness in the last 4 weeks**	**Standardized treatment effects**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Panel A					
Any subsidy	0.158***	0.148	0.035**	0.181**	0.039**
	(0.054)	(0.094)	(0.013)	(0.088)	(0.015)
	[0.042]	[0.183]	[0.039]	[0.121]	
	{0.088}	{0.179}	{0.088}	{0.135}	
R-squared	0.308	0.072	0.091	0.067	0.057
Panel B					
Partial subsidy	0.163***	0.286***	0.047***	0.279***	0.057***
	(0.056)	(0.084)	(0.013)	(0.079)	(0.013)
	[0.029]	[0.022]	[0.006]	[0.020]	
	{0.036}	{0.031}	{0.031}	{0.031}	
Full subsidy	0.138	−0.362**	−0.008	−0.185	−0.029
	(0.089)	(0.171)	(0.020)	(0.182)	(0.027)
	[0.222]	[0.105]	[0.785]	[0.521]	
	{0.503}	{0.349}	{0.781}	{0.586}	
R-squared	0.308	0.084	0.100	0.078	0.068
Panel C					
1/3 subsidy	0.092	0.191	0.033**	0.231*	0.041**
	(0.066)	(0.137)	(0.016)	(0.126)	(0.019)
	[0.238]	[0.235]	[0.070]	[0.119]	
	{0.421}	{0.421}	{0.312}	{0.331}	
2/3 subsidy	0.224***	0.358***	0.057***	0.316***	0.070***
	(0.072)	(0.099)	(0.016)	(0.105)	(0.018)
	[0.017]	[0.009]	[0.016]	[0.032]	
	{0.042}	{0.033}	{0.034}	{0.042}	
Full subsidy	0.148*	−0.348**	−0.005	−0.177	−0.026
	(0.087)	(0.165)	(0.020)	(0.173)	(0.026)
	[0.170]	[0.093]	[0.817]	[0.456]	
	{0.444}	{0.354}	{0.837}	{0.597}	
R-squared	0.314	0.085	0.102	0.078	0.069
Number of observations	658	2666	2661	2564	8309
Control group mean	0.791	0.413	0.013	0.096	0.011
p-values on test of equality:					
Partial subsidy = full subsidy	0.773	0.000	0.008	0.013	0.003
1/3 subsidy = 2/3 subsidy	0.161	0.319	0.236	0.616	0.257
1/3 subsidy = full subsidy	0.418	0.008	0.090	0.014	0.015
2/3 subsidy = full subsidy	0.499	0.000	0.006	0.025	0.003

Note: Panels A, B, and C report the effects of receiving any subsidy, partial and full subsidy, and each subsidy level (1/3, 2/3, and full) on health status in the long run. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. Standardized treatment effects are reported in Column 5. *p*-values for the equality of effect estimates for various pairs of treatment groups are also presented. Robust standard errors clustered at community level are reported in parentheses. Wild-cluster bootstrap *p*-values are reported in square brackets. Family-wise *p*-values are reported in curly brackets.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE A15 Effects on health behaviors.

	Short run	Long run			
	Sleep under mosquito nets	Have mosquito nets	Sleep under mosquito nets	Water safe to drink	Standardized treatment effects
	(1)	(2)	(3)	(4)	(5)
Panel A					
Any subsidy	0.123	−0.028	0.023	−0.057	−0.037
	(0.104)	(0.096)	(0.121)	(0.048)	(0.046)
	[0.251]	[0.839]	[0.875]	[0.289]	
		{0.933}	{0.933}	{0.588}	
R-squared	0.233	0.258	0.235	0.257	0.172
Panel B					
Partial subsidy	0.098	0.039	0.036	−0.071	−0.018
	(0.113)	(0.094)	(0.123)	(0.045)	(0.044)
	[0.457]	[0.758]	[0.806]	[0.149]	
		{0.926}	{0.926}	{0.522}	
Full subsidy	0.227*	−0.269**	−0.044	−0.014	−0.117**
	(0.118)	(0.106)	(0.118)	(0.068)	(0.051)
	[0.113]	[0.064]	[0.749]	[0.878]	
		{0.241}	{0.946}	{0.946}	
R-squared	0.247	0.318	0.259	0.275	0.179
Panel C					
1/3 subsidy	0.020	0.146	0.072	−0.054	0.021
	(0.110)	(0.117)	(0.127)	(0.057)	(0.047)
	[0.886]	[0.343]	[0.664]	[0.394]	
		{0.716}	{0.724}	{0.724}	
2/3 subsidy	0.158	−0.065	0.009	−0.087*	−0.055
	(0.141)	(0.089)	(0.131)	(0.044)	(0.049)
	[0.396]	[0.567]	[0.959]	[0.061]	
		{0.796}	{0.956}	{0.355}	
Full subsidy	0.238**	−0.294***	−0.050	−0.017	−0.127**
	(0.118)	(0.097)	(0.120)	(0.068)	(0.051)
	[0.088]	[0.022]	[0.723]	[0.829]	
		{0.143}	{0.931}	{0.931}	
R-squared	0.252	0.333	0.260	0.276	0.182
Number of observations	1422	1101	1092	497	2069
Control group mean	0.447	0.290	0.661	0.080	0.007
p-values on test of equality:					
Partial subsidy = full subsidy	0.274	0.001	0.179	0.166	0.003
1/3 subsidy = 2/3 subsidy	0.303	0.043	0.382	0.482	0.008
1/3 subsidy = full subsidy	0.096	0.0001	0.131	0.490	0.00004
2/3 subsidy = full subsidy	0.544	0.011	0.340	0.106	0.049

Note: Health behaviors are measured for those aged 12 years and above. Dependent variable in Column 4 is an indicator variable of whether a household member does anything to their water to make it safe to drink. Panels A, B, and C report the effects of receiving any subsidy, partial and full subsidy, and each subsidy level (1/3, 2/3, and full), respectively. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. Standardized treatment effect in the long run is reported in Column 5. *p*-values for the equality of effect estimates for various pairs of treatment groups are also presented. Robust standard errors clustered at community level are reported in parentheses. Wild-cluster bootstrap *p*-values are reported in square brackets. Family-wise *p*-values are reported in curly brackets.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

APPENDIX B

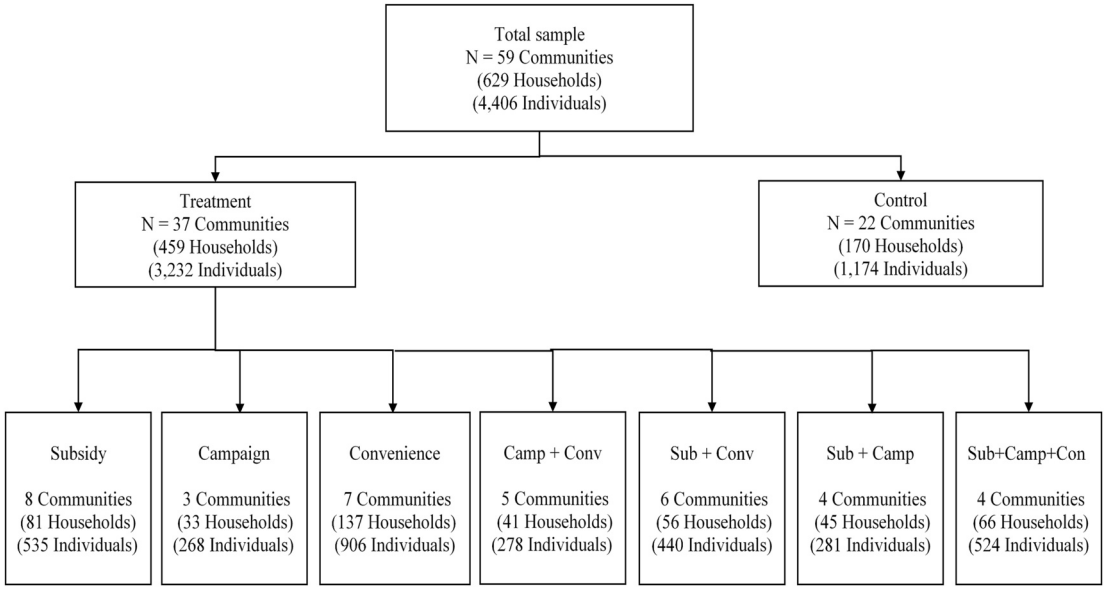


FIGURE B1 Original study design.

TABLE B1 Effects of the original interventions on enrollment.

	Enrollment	
	Short-run	**Long-run**
	(1)	**(2)**
Subsidy only	0.377***	0.149**
	(0.048)	(0.074)
Campaign only	0.126*	0.040
	(0.068)	(0.066)
Convenience only	0.001	0.202***
	(0.066)	(0.073)
Campaign & convenience	0.198	0.171
	(0.151)	(0.155)
Subsidy & convenience	0.305***	0.147**
	(0.080)	(0.063)
Subsidy & campaign	0.521***	0.091
	(0.070)	(0.099)
Subsidy & Camp & Conven	0.447***	0.400***
	(0.063)	(0.084)
R-squared	0.328	0.160
Mean	0.504	0.379
Control group mean	0.272	0.230
Number of observations	4380	3590
p-value on test of equality		
Sub + Camp = Sub & Camp	0.855	0.455
Sub + Conv = Sub & Conv	0.465	0.065

TABLE B1 (Continued)

	Enrollment	
	Short-run	**Long-run**
	(1)	**(2)**
Camp + Conv = Camp & Conv	0.698	0.705
Sub + Camp + Conv = Sub & Camp & Conv	0.600	0.943

Note: This table presents the effects of original intervention on enrollment in health insurance in short and long run. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. *p*-values for the equality of effect estimates are also presented. Robust standard errors clustered at the community level are reported in parentheses.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE B2 Effects on enrollment with restricted sample.

	Enrollment	
	Short-run	**Long-run**
	(1)	**(2)**
Panel A		
Any subsidy	0.410***	0.144*
	(0.045)	(0.078)
R-squared	0.407	0.228
Panel B		
Partial subsidy	0.395***	0.100
	(0.048)	(0.071)
Full subsidy	0.483***	0.351***
	(0.088)	(0.111)
R-squared	0.408	0.239
Panel C		
1/3 subsidy	0.366***	0.144*
	(0.088)	(0.084)
2/3 subsidy	0.416***	0.069
	(0.064)	(0.069)
Full subsidy (free)	0.483***	0.352***
	(0.087)	(0.111)
R-squared	0.408	0.240
Mean	0.405	0.291
Control group mean	0.272	0.233
Number of observations	1614	1273

Note: This table corresponds to Table 2, but the sample is restricted to subsidy only and control groups. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. Robust standard errors clustered at community level are reported in parentheses.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE B3 Effects on health care utilization with restricted sample (short run).

	Short run				
	Visited health facility in last 4 weeks	Visited health facility in last 6 months	# of visits in last 4 weeks	Visited facility for malaria treatment in the last 4 weeks	Standardized treatment effects
	(1)	(2)	(3)	(4)	(5)
Panel A					
Any subsidy	−0.010	−0.012	−0.006	0.011	0.0003
	(0.010)	(0.021)	(0.025)	(0.008)	(0.011)
R-squared	0.121	0.139	0.143	0.113	0.093
Panel B					
Partial subsidy	−0.012	−0.007	−0.003	0.015	0.003
	(0.013)	(0.022)	(0.028)	(0.010)	(0.013)
Full subsidy	0.000	−0.037	−0.022	−0.010	−0.013
	(0.018)	(0.045)	(0.018)	(0.013)	(0.018)
R-squared	0.121	0.139	0.143	0.114	0.093
Panel C					
1/3 subsidy	−0.019	−0.017	−0.025	0.016	0.0002
	(0.021)	(0.023)	(0.039)	(0.012)	(0.018)
2/3 subsidy	−0.006	0.001	0.014	0.013	0.005
	(0.015)	(0.031)	(0.032)	(0.011)	(0.015)
Full subsidy	0.000	−0.037	−0.022	−0.010	−0.013
	(0.018)	(0.045)	(0.017)	(0.013)	(0.018)
R-squared	0.121	0.139	0.144	0.114	0.093
Control group mean	0.038	0.101	0.033	0.018	−0.016
Number of observations	1200	1566	1196	1263	4900

Note: This table corresponds to Table 5, but the sample is restricted to subsidy only and control groups. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. Robust standard errors clustered at community level are reported in parentheses.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE B4 Effects on health care utilization with restricted sample (long run).

	Long run				
	Visited health facility in last 4 weeks	Visited health facility in last 6 months	# of visits in last 4 weeks	Visited facility for malaria treatment in the last 4 weeks	Standardized treatment effects
	(1)	(2)	(3)	(4)	(5)
Panel A					
Any subsidy	0.040***	0.093***	0.030**	0.027*	0.054***
	(0.013)	(0.025)	(0.012)	(0.014)	(0.014)
R-squared	0.109	0.124	0.107	0.105	0.114
Panel B					
Partial subsidy	0.044***	0.084***	0.032**	0.029**	0.056***
	(0.013)	(0.020)	(0.012)	(0.014)	(0.014)
Full subsidy	0.017	0.138**	0.021	0.017	0.042
	(0.018)	(0.057)	(0.019)	(0.018)	(0.027)
R-squared	0.110	0.126	0.107	0.105	0.114

TABLE B4 (Continued)

	Long run				
	Visited health facility in last 4 weeks	**Visited health facility in last 6 months**	**# of visits in last 4 weeks**	**Visited facility for malaria treatment in the last 4 weeks**	**Standardized treatment effects**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Panel C					
1/3 subsidy	0.011	0.067**	0.010	0.012	0.034***
	(0.010)	(0.025)	(0.009)	(0.009)	(0.011)
2/3 subsidy	0.070***	0.096***	0.048**	0.042**	0.074***
	(0.018)	(0.031)	(0.018)	(0.020)	(0.024)
Full subsidy	0.017	0.138**	0.021	0.017	0.042
	(0.018)	(0.057)	(0.019)	(0.018)	(0.027)
R-squared	0.118	0.126	0.111	0.108	0.116
Control group mean	0.014	0.044	0.011	0.009	−0.016
Number of observations	1236	1546	1238	1236	4944

Note: This table corresponds to Table 6, but the sample is restricted to subsidy only and control groups. All regressions include a standard set of covariates (individual, household, and community) and baseline measure of dependent variable. Robust standard errors clustered at community level are reported in parentheses.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE B5 Replication of Table 2 with full sample and additional controls (*Campaign* and *Convenience*).

	Enrollment	
	Short-run	**Long-run**
	(1)	**(2)**
Partial subsidy	0.311***	0.078
	(0.055)	(0.078)
Full subsidy	0.384***	0.140*
	(0.059)	(0.083)
R-squared	0.319	0.155
Mean	0.504	0.379
Control group mean	0.272	0.230
Number of observations	4380	3590
p-values on test of equality:		
Partial subsidy = full subsidy	0.179	0.327

Note: This table repeats the analysis done in Table 2 for partial and full subsidy (Panel B). This table differs from Table 2 in two dimensions: we use full sample—not restricted to respondents who received subsidy—and we add *Campaign* and *Convenience* indicators as controls.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE B6 Replication of Table 5 with full sample and additional controls (*Campaign* and *Convenience*).

	Short run				
	Visited health facility in last 4 weeks	**Visited health facility in last 6 months**	**# of visits in last 4 weeks**	**Visited facility for malaria treatment in the last 4 weeks**	**Standardized treatment effects**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Partial subsidy	−0.007	0.007	−0.005	0.009	0.004
	(0.009)	(0.019)	(0.019)	(0.007)	(0.010)
Full subsidy	0.013	0.018	0.012	0.004	0.017
	(0.022)	(0.029)	(0.036)	(0.011)	(0.021)
R-squared	0.100	0.105	0.048	0.045	0.053
Control group mean	0.038	0.101	0.033	0.018	−0.013
Number of observations	3477	4285	3476	3629	14,192
p-values on test of equality:					
Partial subsidy = full subsidy	0.348	0.666	0.625	0.653	0.503

Note: This table repeats the analysis done in Table 5 for partial and full subsidy (Panel B). This table differs from Table 5 in two dimensions: we use full sample—not restricted to respondents who received subsidy—and we add *Campaign* and *Convenience* indicators as controls.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE B7 Replication of Table 6 with full sample and additional controls (*Campaign* and *Convenience*).

	Long run				
	Visited health facility in last 4 weeks	**Visited health facility in last 6 months**	**# of visits in last 4 weeks**	**Visited facility for malaria treatment in the last 4 weeks**	**Standardized treatment effects**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Partial subsidy	0.040***	0.106***	0.035***	0.034**	0.064***
	(0.014)	(0.023)	(0.013)	(0.014)	(0.017)
Full subsidy	−0.020	−0.003	−0.023	−0.024	−0.025
	(0.015)	(0.043)	(0.017)	(0.016)	(0.024)
R-squared	0.069	0.081	0.054	0.056	0.062
Control group mean	0.014	0.044	0.011	0.009	−0.028
Number of observations	3616	4256	3640	3616	14,464
p-values on test of equality:					
Partial subsidy = full subsidy	0.002	0.011	0.009	0.005	0.004

Note: This table repeats the analysis done in Table 6 for partial and full subsidy (Panel B). This table differs from Table 6 in two dimensions: we use full sample—not restricted to respondents who received subsidy—and we add *Campaign* and *Convenience* indicators as controls.

* **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.