Health Insurance Provision and Women's Healthcare Utilization: Evidence from the National Health Insurance Scheme in Ghana*

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Abstract

We use women in the Demographic and Health Survey to study the healthcare utilization effects of Ghana's adoption of a National Health Insurance Scheme (NHIS) with district-staggered rollout from 2004 to 2007 and covering over 95% of medical expenditures. First, we exploit variation in NHIS adoption across geographic locations over time to address endogeneity in verified self-reported NHIS participation to study the effect of the insurance on twelve-month healthcare visits. We estimate an average treatment effect of 32 percentage points increase in twelve-month medical care use due to NHIS coverage. We also find differential effects of the insurance on twelve-month medical care use in favor of women with lower years of education, in poor households, and living in rural areas. Second, we leverage the variation in district-staggered adoption of the NHIS to estimate the intent-to-treat effect of the insurance on institutional births and prenatal care visits among women in Ghana using similar women from rural Nigeria as the comparison group. We find that exposure to the NHIS increases the occurrence of institutional births by 6 percentage points and attending prenatal care by 8 percentage points. Altogether, these findings are consistent with evidence from similar programs in developed countries despite relatively low take-up of the NHIS.

1. Introduction

The relative poor maternal health and high child mortality in developing countries compared to advanced nations suggest low medical care among mothers and children (Currie and Gruber, 1996). To address these problems, the United Nations included maternal health improvements and child mortality reductions as two of the eight Millennium Development Goals signed by member countries in 2000. Consequently, several countries implemented health insurance programs to achieve these goals (Cesur et al., 2017). The government of Ghana enacted a National Health Insurance Scheme (NHIS), with a district-level rollout from early 2004 to mid-2007, to address the healthcare market failures from the traditional "cash-and-carry" system (i.e., users bearing the full costs of healthcare utilization) that resulted in low medical care use and poor infant and maternal health.

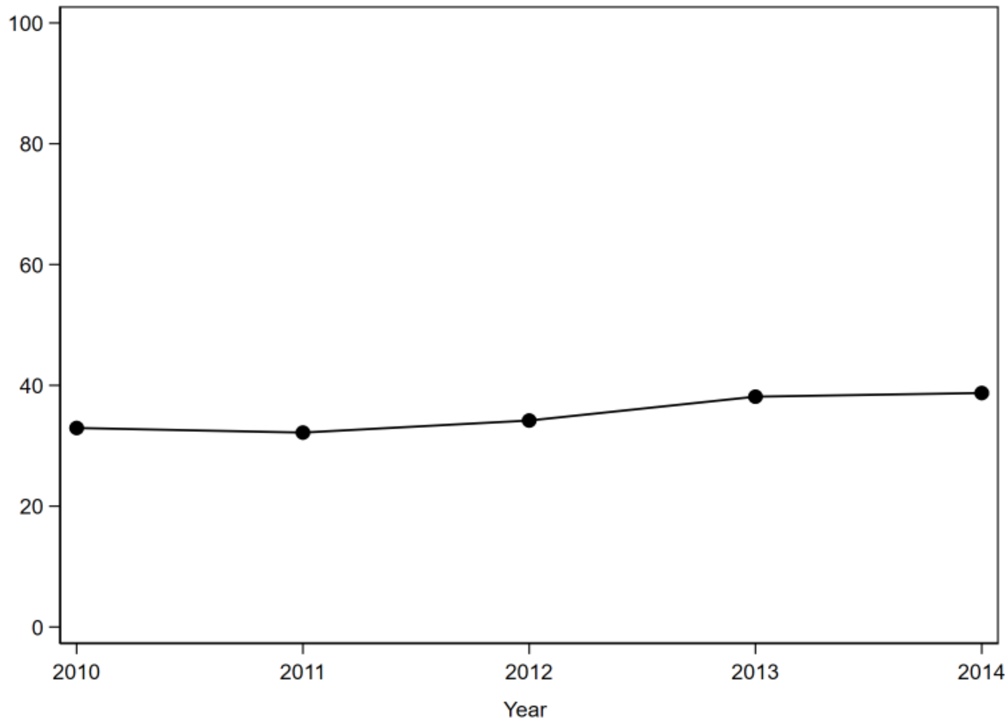
This study estimates the causal effect of the NHIS on healthcare utilization among women in Ghana. We consider three closely related binary outcome measures of healthcare utilization among women of childbearing ages (15-49): any medical care use in the last twelve months, any births in health facilities (or institutional births), and any prenatal care visits in the first four months of pregnancy. Our primary data source is the standard Demographic and Health Survey (DHS), available in many developing countries, such as Ghana and Nigeria. The analytical sample comprises women in the 2003, 2008, and 2014 survey waves. We also use the National Health Insurance Authority's administrative information on the dates on the certificates of commencement of the NHIS issued to the districts before beginning the NHIS.

We analyze the last twelve-month medical care use, available only in survey years, in an instrumental variable framework using district-staggered rollout as an instrument for NHIS participation to address any endogeneity concerns in the NHIS take-up. We jointly model the women's decisions to participate in the NHIS through their eligibility and medical care use behaviors. For the two birth-related outcomes, available in all years from 1998 to 2013, we exploit the variations in the district-staggered adoption of the NHIS in a difference-in-differences (DID) framework to compare the utilization behavior of Ghanaian women to those from rural Nigeria. For most children in the Ghanaian sample, we do not have information on their mothers' insurance participation at the time of birth. We take advantage of the availability of the 2003, 2008, and 2013 DHS survey data for Nigeria to use the women from rural Nigeria—less likely to be affected by any health insurance policy—as a comparison group to provide intent-to-treat estimates of the NHIS on the two understudied birth-related outcomes.

We estimate an average treatment effect of the NHIS on twelve-month healthcare visits to be approximately 32 percentage points increase, which translates into 66%, among the women induced by the NHIS eligibility to obtain coverage. Also, we find that the NHIS differentially impacted twelve-month medical care use among the women based on demographic characteristics and location of residence; the increase in healthcare utilization was higher among poor, rural, and low-educated women. Our intent-to-treat estimates are that the NHIS increases institutional births by 5.3 percentage points (17%) and prenatal care visits by 7.6 percentage points (21%). The government of Ghana also provided free health insurance to pregnant women (popularly known as 'free maternal healthcare policy') starting in July 2008. Our findings show that the new policy increased institutional births by 5.7 percentage points (18%) and prenatal care visits by 3.5 percentage points (10%).

Our study extends the literature in three ways. First, studying the impact of the NHIS on maternal healthcare use is important because it provides evidence on the extent to which the NHIS improved medical care use among mothers to achieve the MDG goals of improving maternal health and decreasing infant mortality. The effectiveness of health insurance programs from developed countries [e.g., Affordable Care Act in the United States (Courtemanche et al., 2017)] may not generalize to similar programs in developing countries (Chen et al., 2007) since health insurance in underdeveloped countries can be influenced by several factors, including cultural beliefs and public perception. Importantly, the impacts of health insurance on various outcomes in less developed countries is inconclusive (Bagnoli, 2019). Several studies have demonstrated positive effects of health insurance on healthcare use and health in different countries (for example, see Aggarwal (2010) in India, Hamid et al. (2011) in Bangladesh, and Bagnoli (2019) in Ghana) while other studies show no meaningful impact of health insurance on healthcare use or health (e.g., see Giuntella and Lonsky (2020) in Mexico and Chen and Jin (2012) in China). The theoretical model for demand for health suggests that as health investment input prices fall, their demand rise, increasing health investments (Grossman, 1972); however, government provision of highly subsidized NHIS could not induce most individuals in Ghana to take up the NHIS. Even after seven years of nationwide implementation, the overall coverage rate was approximately 40% in 2014 (see Figure 1). It suggests that the NHIS in Ghana is unique; therefore, the findings from this study will advance the literature on the impacts of health insurance in developing countries.

Second, we address critical methodological issues regarding the endogeneity of health insurance choice and the design of the NHIS to interpret our estimates causally. By design, the NHIS participation is endogenous. Because of universal eligibility and voluntary participation, individuals with poor health expected to be sicker are more likely to enroll in the NHIS. Besides, behavioral responses in the form of ex-ante and ex-post moral hazards can be additional sources of endogeneity (Yilma et al., 2012). In the absence of cost-sharing measures and cap on healthcare utilization after gaining coverage, participants of the NHIS can engage in risky behaviors, underinvest in other health inputs, or use healthcare excessively (Debpuur et al., 2015). We use variations in district rollout of the NHIS to address the endogeneity concerns



Source: Nsiah-Boateng and Aikins (2018)

Figure 1: Trend of NHIS coverage rate in Ghana, 2010 – 2014.

as used in similar studies (Abrokwah et al., 2019; Strupat and Klohn, 2018).

Another issue with the design of the NHIS is that since everyone is eligible for the insurance and rollouts across districts were sharp, it renders any pre-post comparison using non-experimental data ineffectual in isolating the causal effect of the NHIS from the general time trend.[1] The methods used in this study allow us to address the endogeneity concerns and disentangle the causal effect of the NHIS from the national trends in healthcare utilization.

Finally, our study provides the most credible causal estimate on the impacts of the NHIS on medical care use after overcoming misreporting in self-reported insurance participation.[2] In the absence of administrative data, studies that rely on self-reported binary program participation information in surveys are subject to potential misreporting, which can introduce nontrivial biases into the estimates (Wossen et al., 2019; Nguimkeu et al., 2019). Responses to

[1]Several surveys in Ghana occurred either before or after the rollout period. Since all Ghanaian citizens were eligible for the NHIS, there is no variation in the treatment of the NHIS across districts over time in most surveys.

[2]A misclassification of NHIS participation occurs when some individuals report having NHIS coverage when they are not ("false positives") or report as uninsured when they have NHIS coverage ("false negatives").

the NHIS participation question in the DHS data were not exceptional. Similar studies that used the DHS data failed to investigate potential misreporting in the data (Abrokwah et al., 2014, 2019; Mensah et al., 2010); however, our analyses demonstrate evidence of misclassification in the NHIS participation responses. By addressing the misreporting concerns, we provide a credible causal estimate of the impacts of the NHIS on medical care use.

We organize the remaining sections of the study as follows. Section 2 provides a comprehensive literature review on the effects of the NHIS on healthcare utilization. We discuss the political economy of Ghana and background information on the NHIS in Section 3. The data description is in Section 4, followed by the description of the study design used to identify the causal impact of the NHIS on healthcare utilization in Section 5. We present our results in Section 6. Section 7 discusses the results and concludes the study.

2. Literature Review

Some studies have shown correlations between the NHIS and healthcare utilization; however, they failed to address endogeneity concerns in the NHIS participation (Agbanyo, 2020; Brugiavini and Pace, 2016; Dzakpasu et al., 2012). The NHIS characterized by voluntary participation could lead to self-selection based on individual unobserved heterogeneity such as health status, preferences, and risk behaviors, which affect their insurance participation and healthcare utilization decisions. For example, one study finds that households with NHIS coverage are less likely to take malaria preventative measures compared to those without insurance (Yilma et al., 2012); another study demonstrates abuses of the NHIS through unnecessary healthcare utilization and impersonation (Debpuur et al., 2015).

To the best of our knowledge, we find only three studies on the NHIS that relate to our study in part (Abrokwah et al., 2019; Bagnoli, 2019; Abrokwah et al., 2014). Two of these studies used district-level variation in the timing of NHIS rollout to address endogeneity in NHIS participation.[3] Abrokwah et al. (2014) estimate the effects of the NHIS on prenatal care visits using two-parts models and find that the NHIS increases prenatal care visits. A limitation of the study is that they use data from only the 2005/6, which restricts their sample to a few pregnant women within one year before the survey interview date, making their results less generalizable. Our study overcomes this external validity concern by using a large sample of women from several districts with pregnancy outcomes occurring from 1998 – 2013. The second study finds strong evidence that participation in the NHIS increases formal and informal care use (Abrokwah et al., 2019). Our study differs from Abrokwah et al. (2019) since we estimate the impact of the NHIS on different and specific healthcare utilization outcomes. Third, Bagnoli (2019) used propensity score matching to compare health outcomes of insured and uninsured children. Our study focuses on healthcare use that complements the finding of improvement of child health in Bagnoli (2019).

Two studies use a propensity score matching method to estimate the causal impact of the NHIS on healthcare utilization, but with limitations. Bonfrer et al. (2016) study maternal healthcare utilization using the 2008 wave of the DHS survey data and find that NHIS participation increases prenatal and postnatal care visits, but decreases the number of unwanted pregnancies, and has no effect on child vaccination. The study assumption of women's insurance status at the interview date being representative of their NHIS participation status when the under two-year-old children were in utero could bias the estimates. For such an assumption, standard errors-in-variable methods cannot easily overcome non-classical measurement errors that the misclassified binary endogenous NHIS participation potentially introduces into their models. (We describe this in detail in Section 4.) While the study reported a 39.8% NHIS

[3] We also use a similar identification strategy; however, while these studies use a 0/1 instrumental variable (IV) for NHIS participation, we improve on it by using staggered adoption of the NHIS to construct our instrument for NHIS participation.

coverage among women in the 2008 DHS survey, we demonstrate from the same data that only 25% of the women had unexpired NHIS coverage at the interview date.

Mensah et al. (2010) surveyed 2,000 women from two of the ten administrative regions of Ghana but could only use 625 women in a propensity score matching framework to evaluate the impact of gaining health insurance on healthcare utilization. They find that the women who enroll in the NHIS are more likely to utilize prenatal care services and deliver in health facilities. Their results may not be generalizable because they used a few women from only two regions for their analysis. Our study builds on this literature to use data from all administrative regions of Ghana from 1998 to 2013 to analyze the impacts of the NHIS on these outcomes.

Using a randomized control trial, Ansah et al. (2009) and Powell-Jackson et al. (2014) study the effects of free NHIS enrollment on healthcare utilization among under five-year-old children.[4] Powell-Jackson et al. (2014) find that the provision of free NHIS increases the number of annual visits to clinics but reduces informal care use and financial stress, including out-of-pocket spending and borrowing, but do not affect the number of annual hospital visits and health outcomes of children. Ansah et al. (2009) find similar estimates that providing children with free access to healthcare through the NHIS increases formal healthcare utilization and decreases informal healthcare use. Our study differs from these studies in two ways. First, although both studies use experimental data that may be preferred to survey data, their data from the few poor rural districts may not be representative of the Ghanaian population, making external validity a concern. Our study overcomes this concern by using data from several districts in Ghana. Second, while these studies focus on the outcomes of under-five-year-old children, we consider women and their pregnancy-related healthcare utilization outcomes, which may differ from the healthcare utilization behavior of under-five-year-old children.

[4]In an experiment, Powell-Jackson et al. (2014) provided randomly assigned treated households in one poor rural district in Southern Ghana with free healthcare by paying their enrollment fees for the NHIS. Similarly, Ansah et al. (2009) provided free health insurance to some children in two districts to compare their outcomes to those of the control group.

3. The Political Economy of Ghana and the NHIS

Financed by tax, the Government of Ghana, as part of its 10-year development plan after independence in 1957, included expansion of existing public health facilities, reduction of healthcare user fees, and free medical care in most cases (Arhinful, 2003). Because of a series of political unrest between 1965 and 1982[5] and worsened economic conditions, subsidizing the healthcare industry was not sustainable (Fusheini et al., 2012; Yevutsey and Aikins, 2010). Additionally, prolonged drought, widespread of bush fires that affected agriculture, leading to famine, further worsened economic conditions. It forced Ghana to adopt the International Monetary Fund and World Bank-sponsored structural adjustment program in 1983. Subsequently, Ghana cut its fiscal expenditure and abolished all healthcare subsidies through the adjustment program (Fusheini et al., 2012; Ankomah, 2004) and instituted user fees on medical care use to generate revenue to finance the healthcare industry. The charging of user fees continued through 1992 when another restructuring of the healthcare industry occurred to impose the full costs of using public health services on consumers, a system popularly known as the "cash and carry." The new healthcare financing system increased the cost of using medical care tremendously, which resulted in low participation in formal healthcare use, with most Ghanaian residents substituting medical care use for alternatives, including self-medication, traditional medicine, and spiritual healing (Fusheini et al., 2012). Because of these issues, maternal healthcare utilization were low and maternal and infant mortality was high. For example, only 25% of pregnant women had at least one antenatal care visit in 1998, and under five-year-old mortality rate was 108 deaths per $1,000$ live births (Ghana Statistical Service, 1999).

With support from the United States Agency for International Development, the Government of Ghana implemented the NHIS in early 2004 to address healthcare market failures

[5]During this period, military men overthrew governments.

created by the "cash and carry" system. Before instituting the NHIS, a few private, employer-based, and community-based health insurance schemes were available but were limited to a few people and areas,[6] and approximately only 3% of the Ghanaian population were insured in 2003.[7] The scope of the NHIS coverage is about 95% expenditure on all disease conditions, inpatient and outpatient services, and drugs.[8] As a complementary policy, a free maternal healthcare policy was implemented in July 2008 to provide pregnant women with free NHIS coverage for pregnancies and three months postpartum (Dalinjong et al., 2018).

The rollout of the NHIS occurred at the district level, which is the third administrative division of Ghana. Districts that wanted to participate in the NHIS needed at least $2,000$ individuals to register initially, subject to review every six months. All residents of districts that adopted the NHIS were eligible for participation in their districts, and enrollment occurs throughout the year with a waiting period of three months. The decentralized participation decision among districts created staggered rollouts of the NHIS from early 2004 to mid 2007 (Figure 2). By design, the NHIS has two types of costs– registration fee and premium. Districts were required to charge prices based on the consumer's "ability to pay," ranging from ₵$7,000$ to ₵$50,000$ (i.e., ¢$77-\$5.52$ in 2005 U.S. dollars) for the registration fee and ₵$72,000$ to ₵$480,000$ (i.e., $\$7.95 - \$53.03$ in 2005 U.S. dollars) for the premium (Abrokwah et al., 2019; Blanchet et al., 2012).[9] Because districts could not verify incomes among informal sector employees, they charged flat rates for both the premium and registration fees.[10]

The government of Ghana charges different premiums based on participant's economic status. Individuals with mental disorders, indigents, and those on government cash transfer

[6] Atim et al. (2001) provides a list of all the communities with healthcare financing schemes before the implementation of the NHIS.

[7] See DHS 2003 report at `https://dhsprogram.com/pubs/pdf/FR152/FR152.pdf`.

[8] For details about covered health conditions, see from `http://www.nhis.gov.gh/benefits.aspx`.

[9] We used the 2005 average cedi (i.e., the old Ghanaian currency) to the U.S. dollar exchange rate of ₵9,051.95 = \$1. Ghana redenominated its cedi currency in July 2007 at a rate of ₵10,000=GH₵1.

[10] Because many people in Ghana work in the informal sector and do not file taxes annually, it is almost impossible to verify their self-reported income. Most districts charged a fixed premium of ₵$72,000$ despite the income disparities among participants (Abrokwah et al., 2014).

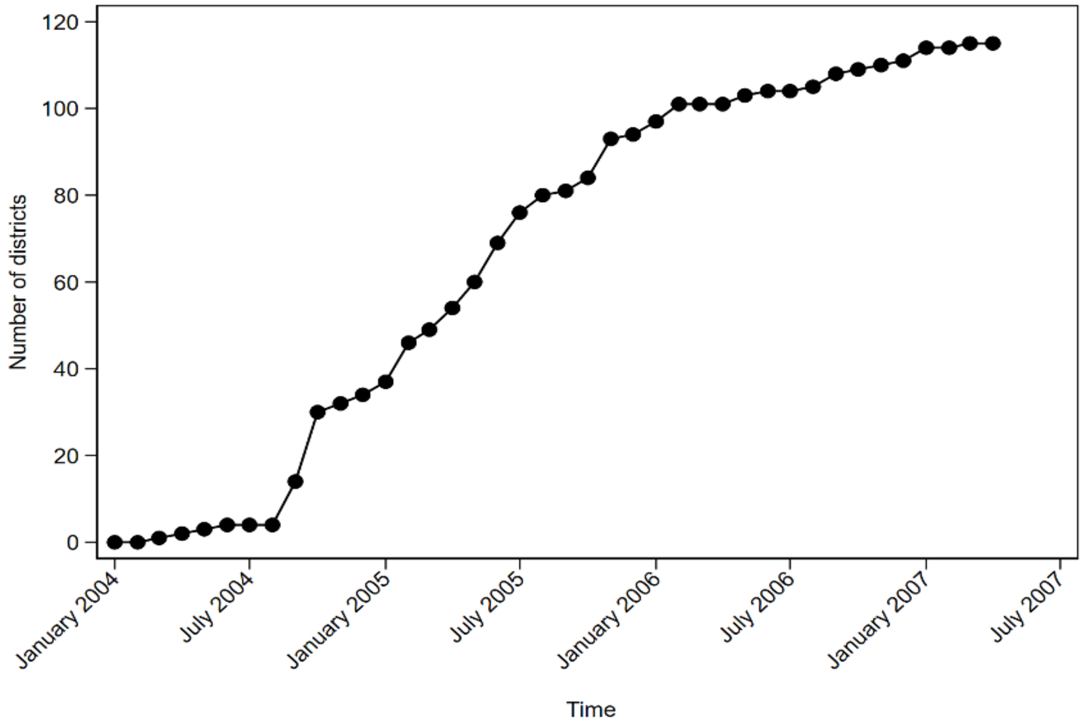


Figure 2: Timing of district adoption of the NHIS, 2004 – 2007

programs are eligible for free coverage. The formal sector employees, Social Security and National Insurance Trust (SSNIT) pensioners, adults over 70 years, and children under 18 years whose parents have coverage receive a partial subsidy and pay only the registration fee. The remaining informal sector employees face the full price of the NHIS described earlier.

Because premium payments alone cannot finance the highly subsidized insurance program, the government of Ghana raises funds from other sources to support the NHIS. The largest source of funds comes from National Health Insurance Levy (NHIL), a 2.5% excise tax on specific goods and services. Another source of funds for the NHIS is a 2.5 percentage points deduction of formal employees' SSNIT monthly contributions. In context, the distribution of NHIS finance sources in 2013 consisted of 71.9% from NHIL levy, 20.0% from SSNIT contributions, 4.7% from investments of NHIS funds, and only 3.4% from premiums.[11]

Grossman (1972) canonical model for demand for health suggests that as prices of health

[11]See National Health Insurance Authority annual report for 2013 at http://www.nhis.gov.gh/files/2013%20Annual%20Report-Final%20ver%2029.09.14.pdf.

inputs such as the NHIS decreases, health investments rise. However, participation in health insurance was lower than 40% even after a decade of implementation despite all the subsidies that reduced premiums below actuarially fair price (Figure 1). Details of the possible reasons for the low take-up of the NHIS are provided in the Online Appendix, Section A.

4. Data

We use the restricted geocoded standard Demographic and Health Survey (DHS) for Ghana and Nigeria as our data source. Supported by the U.S. Agency for International Development, the DHS program has assisted over 400 surveys in about 90 developing countries to conduct irregular, but high-frequently in-depth household-level surveys of health since the late 1970*s* (Young, 2013). Ghana and Nigeria have benefited from the DHS program since 1988 and 1990, respectively. The surveys collect, analyze, and distribute accurately, a wide range of standard information across countries. At the country level, the DHS has nationally representative data on maternal healthcare utilization, allowing us to use it for analysis. All data sets from the DHS surveys are publicly available except for information on HIV and residential location. We pool the 2003, 2008, and 2014 survey waves from Ghana as well as 2003, 2008, and 2013 survey waves from Nigeria for the analysis. DHS surveys cover many families and have high response rates, as the Ghanaian waves include 6,200, 12,000, and 11,800 households interviewed in 2003, 2008, and 2014, respectively and the response rates were at least 95.7%. Similarly, the DHS survey in Nigeria recruited 7,225, 34,070, and 38,522 households in 2003, 2008, and 2013, respectively, with a minimum response rate of 98.3%.

The DHS administers three main questionnaires with different eligibility criteria. Eligibility for the men's sample is ages 15–59, while that of the women is ages 15–49. In the women questionnaire, the survey collects a broad set of questions on health insurance and healthcare utilization. We construct a binary indicator variable for past twelve-month medical care use as one outcome.[12] For under five-year-old children, detailed information on their places of births is available. The surveys also provide a history of the mother's last birth prenatal care visits for under five-year-old children.[13] We link the women and child's samples to create indicator variables for prenatal care visits and births in health facilities as two other outcomes.

Woman's NHIS participation status when utilizing healthcare is the key variable of interest. In the DHS survey, the women provide information on their health insurance coverage at the interview date. The surveys also ask additional questions to identify the type of health insurance plan that respondents patronize. Insurance plans available in the DHS surveys from Ghana are the NHIS, employer-based health insurance, mutual health organization (or community-based insurance), private health insurance, and commercial health insurance. However, over 98% of insurance participants obtained NHIS coverage in our sample. Consequently, we drop the women in the 2008 and 2014 surveys with insurance coverage from other types to focus on just the NHIS.[14] One advantage of the DHS survey is that it verifies the validity of the responses to the NHIS participation questions. Interviewers ask the women to provide their valid NHIS cards if they claim to have coverage.[15] We construct the NHIS participation variable to include only the women whose NHIS cards were verified to avoid misclassification.[16]

Our second data source comes from the National Health Insurance Authority (NHIA),

[12]We are unable to use the men's sample in this study because there is no information on their healthcare utilization.

[13]We use the date of birth to create outcomes from 1998 - 2013. However, we do not have enough samples in 2004 and 2019 for individuals from Ghana. Since rollouts of the NHIS began in 2004 and a few districts enrolled, we add the few individuals from 2004 to the 2003 samples, and 2009 to 2008 for the prenatal care visits outcome.

[14]However, we use private health insurance enrollment before the NHIS for identification purposes.

[15]In the questionnaires, respondents answer questions on health insurance participation status. The follow-up question is to identify the type of insurance that they purchase if the answer to the previous questions is "Yes." The next question probes to verify from those who claim to be NHIS participants if they have valid NHIS cards. Because the interviewers want to confirm the validity of their responses, they check the NHIS cards and categorize them as follows: "Yes, card seen," "Yes, card not seen," and "No." The last question that validates these answers is to determine why some of the NHIS participants did not hold valid NHIS cards. In our sample, most respondents either did not renew their NHIS cards on time or were new participants, but in the three-month waiting period.

[16]By defining the NHIS participants to include only women with verified and valid NHIS cards, we replicate the statistics in Figure 1, constructed from the National Health Insurance Authority's administrative data. For example, Figure 1 shows that about 39% of the Ghanaian population participated in the NHIS in 2014. We find from our data that about 35.2% of the women had NHIS coverage in 2014. It suggests that our data is representative of the Ghanaian population. On the contrary, other studies of the NHIS report higher insurance coverage rates (e.g., 60% coverage rate among women in 2014 in Abrokwah et al. (2019) and 54% insured rate among children in 2011 in Bagnoli (2019)). These studies used dataset that did not verify NHIS participation status of respondents.

which provided information on the certificates of commencement of NHIS for districts. We obtained commencement dates for 111 out of the 130 administrative districts of Ghana (Figure 2). We construct our instrument for insurance participation, the years of eligibility (exposure) of the NHIS, based on the commencement date and the interview date. Specifically, we define our instrumental variable (IV) as the number of years the individuals become exposed to the NHIS in their residential districts. We then link the years of NHIS eligibility to the individual-level data from the DHS based on the district of residence. The distribution of the IV shows that among the women exposed to the NHIS, years of NHIS eligibility range from one year and five months to nine years and six months (Figure 3). Notice that the gaps in the IV distributions come from the gaps in the surveys.

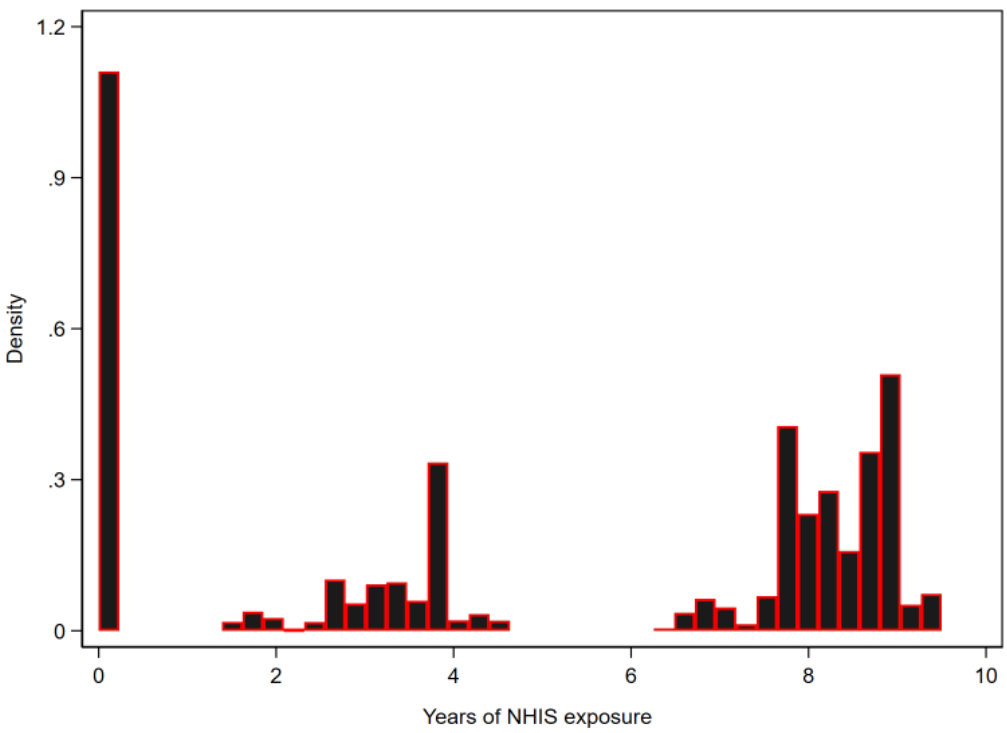


Figure 3: Distribution of NHIS years of exposure (eligibility) among women

A limitation of the DHS data is that information on women's insurance participation outcomes is known only in the survey year. For under-five-year-old children whose information on places of birth and mother prenatal care visits during pregnancy is available in off-survey years, we do not have information on mothers' insurance participation statuses at the time of conception or birth. Unfortunately, we lose most of the women in our sample, resulting in low statistical power, when we use only the under one-year-old children whose mother's NHIS participation outcomes are available. Consequently, we are unable to use the DHS data from Ghana alone to estimate the impacts of the NHIS on prenatal care visits and institutional births unless we assume that the mother's enrollment status at the time of the interview is representative of the enrollment status during pregnancy or birth. To overcome concerns of making assumptions that can create non-classical measurement errors in the NHIS participation variable, we use similar mothers from rural Nigeria to complement the women from Ghana to analyze the births in facilities and prenatal care visits.

5. Empirical Strategies

Consider the structural equation for a binary choice healthcare utilization outcome below:

$$Y_{idt} = \mathbf{1}(\beta_0 + \beta_1 I_{idt} + \mathbf{\Lambda X_{idt}} + \boldsymbol{\gamma_d} + \boldsymbol{\tau_t} + \epsilon_{idt} > 0), \tag{1}$$

where $\mathbf{1}(\bullet)$ is the indicator function taking the value of 1 if its argument is true and 0 otherwise, Y_{idt} represents the outcome (any healthcare visits in the past twelve months, any birth in a health facility, or any prenatal care visit) for individual i in district d at time t. The variables, I_{idt} and ϵ_{idt}, represent NHIS participation outcome and the error term, respectively, for individual i in district d at time t. The observed insurance participation, I_{idt}, takes the value of 1 if the individual has NHIS coverage and 0 otherwise. The vector $\mathbf{X_{idt}}$ represents the set of individual and household characteristics such as age, gender, occupation, education, wealth index, and a dummy for residential locations (rural vs. urban). We include a vector of district and year fixed effects (i.e., γ_d and τ_t, respectively) to account for district time-invariant characteristics and national trends that contribute to changes in Y_{idt} other than the NHIS.

Our objective is to estimate causally the value of β_1, which represents the impact of the NHIS, for each outcome of interest. However, an identification challenge is the issue of endogeneity in the NHIS participation outcome. As discussed earlier, I_{idt} has at least two significant sources of endogeneity. First, adverse selection stems from the fact that some individuals make participation decisions based on their health conditions. Because everyone in Ghana is eligible for the NHIS, sicker individuals are more likely to obtain NHIS coverage. Given that there is open enrollment throughout the year with only a three-month waiting period, individuals can strategically make participation decisions. Second, the issue of "ex-ante moral hazard," which means lower investments in health and behavioral changes in anticipation of using health insurance to access healthcare, is shown to be another source of endogeneity (Debpuur et al., 2015; Yilma et al., 2012). We address these concern to interpret $\hat{\beta}_1$ causally.

For the outcome of twelve-month medical care use, observed only in the survey years, we use an instrumental variable (IV) strategy to address the endogeneity issues in NHIS participation. We specify the insurance participation equation as follows.

$$I_{idt} = \mathbf{1}(\alpha_0 + \alpha_1 \mathrm{Z_{dt}} + \boldsymbol{\theta}\mathbf{X_{idt}} + \eta_{idt} > 0), \tag{2}$$

where the variable η_{idt} represents an independently and identically distributed error term for individual i in district d at time t. The variable of interest in equation (2) is Z_{dt}, which denotes our instrument and varies across districts and over time (see Figure 2). We test the hypothesis that an additional year of NHIS eligibility induces participation in the NHIS among women.

Because the outcome (Y_{idt}) and the endogenous regressor (I_{idt}) are binary variables, there can be serious methodological concerns associated with a linear IV model. At best, the linear IV model may only approximate the average marginal effects, which sometimes turns out to be poor in practice (Wooldridge, 2010, pp. 596-597). The reason is that the conditional mean functions in equations (1) and (2) can be highly nonlinear, leading to a significant difference between the derivatives of the true nonlinear model and their linear approximation (Lewbel et al., 2012). The linear approximated model can lead to marginal effects that are inconsistent and inefficient estimates of the treatment effects (see details in the Online Appendix, Section B). To address this concern, we follow the estimation approach used by Altonji et al. (2005a) in their catholic schooling study. The study made a distributional assumption of joint normality between error terms in equatons (1) and (2) (i.e., ϵ_{idt} and η_{idt}) and estimated a bivariate probit model where the identification of the parameters comes from the functional form restriction and the excluded instrument (i.e., Z_{dt}). Aside from the benefit of getting consistent and efficient marginal effects, a bivariate probit model permits the joint estimation of both the decision to participate in the NHIS through eligibility and its impacts on medical care use. The joint estimation approach prevents potential biases from any unobserved factors common to the NHIS take-up and healthcare utilization decisions (Abrokwah et al., 2019).

For the outcomes of births in health facilities and prenatal care visits, we use a difference-in-differences strategy (described in the Online Appendix, Section C) and women from Rural Nigeria as a comparison group to overcome the endogeneity concerns in NHIS participation.

6. Results

6.1. Effects of the NHIS on Any Twelve-Month Medical Care Use

In Table 1, we report the means and standard deviations of the key variables used to estimate the effects of the NHIS on twelve-month medical use. The sample consists of approximately 15,100 women aged $15 - 49$, with about 3,700 (24.4%) women covered by NHIS, while the remaining $11,400$ (75.6%) women did not have any health insurance coverage. Twelve-month medical care use differs by NHIS coverage. The women with NHIS coverage were 19 percentage points more likely to use medical care than those without health insurance (Panel A). While 32% of the women who used medical care had NHIS coverage, 18% of those who didn't use medical care had health insurance coverage (Panel B). Overall, about half of the women in the sample used medical care in the past twelve months. The women with and without NHIS coverage differ in characteristics (Online Appendix, Table A1). Similarly, the socio-demographic characteristics of women who used medical care differ from those who did not use medical care (Online Appendix, Table A2). Therefore, we include the socio-demographic characteristics in our regressions to account for the observed differences.

Table 1. Means and standard deviations (in parenthesis) of last twelve-month medical care use, insurance coverage, and NHIS exposure among the women in the sample

	Panel A: By health insurance coverage		
	Insured	Uninsured	All women
Twelve-month medical care use	0.62 (0.49)	0.43 (0.50)	0.48 (0.50)
Years of NHIS exposure	7.10 (2.28)	4.47 (3.74)	5.11 (3.62)
Number of observations	3,683	11,429	15,112
	Panel B: By twelve-month medical care use		
	Medical care use	No medical care use	All women
NHIS coverage	0.32 (0.47)	0.18 (0.38)	0.24 (0.43)
Years of NHIS exposure	5.41 (3.53)	4.84 (3.68)	5.11 (3.62)
Number of observations	7,213	7,899	15,112

Table 1 also shows that the years of NHIS eligibility differ by NHIS coverage status and twelve-month medical care use. The women with NHIS coverage had seven years and one month of NHIS exposure, compared to four years and six months of exposure among the women without NHIS coverage. Similarly, the women who used medical care had five years and five months of NHIS eligibility, compared to those without medical care who had four years and ten months of NHIS eligibility. The average duration of NHIS eligibility among all women in the sample is approximately five years and one month.

6.1.1 First Stage Estimates: NHIS Eligibility and Enrollment

The statistics in Table 1 suggest that the unconditional correlation between NHIS participation and the years of exposure is positive. On average, women with higher years of NHIS eligibility were more likely to obtain NHIS coverage than their counterparts with lower years of exposure. We formally test this correlation and present the results from linear probability models in Table 2. The specification in the first column excludes all the characteristics (Online Appendix, Table A1) of the women and time components. However, because the distributions of the characteristics between the insured and uninsured women differ significantly, we include them in the specifications in Columns (2) – (4). In the last two columns, we either include survey year fixed effects or a post-NHIS dummy variable to account for trends in national growth.

The estimates from the first stage regression model, with or without the characteristics of the women, but excluding time component, show a strong correlation between NHIS participation and years of eligibility. The statistically significant estimates in Columns (1) and (2) suggest that a one-year NHIS eligibility increases NHIS take-up by 3.6 percentage points. Because the DHS completes surveys in a district within three months, accounting for district and survey fixed effects in the same model leads to a weak first-stage estimate since the NHIS eligibility variable has little within-district variation to exploit among women [Column (3)].

To overcome the challenge of perfect collinearity between years of NHIS eligibility and

Table 2. First stage estimates: Effect of years of NHIS exposure on NHIS participation among women (ages $15-49$) in Ghana using a Linear Probability Model

	(1)	(2)	(3)	(4)
Years of NHIS exposure	0.036***	0.036***	-0.001	0.016***
	(0.003)	(0.003)	(0.028)	(0.003)
Controls	N	Y	Y	Y
Post-NHIS dummy	N	N	N	Y
Survey year fixed effects	N	N	Y	N
F-statistic	198	199	0	30
Number of observations	15,112	15,112	15,112	15,112

Notes: We include the woman's age, place of resident (rural/urban), marital status of woman, pregnancy status, number of births in the last five years, birth history, wealth index, woman's education, woman's occupation, literacy status of woman, ethnicity, religion, and district fixed effects as the controls in each specification. We report heteroscedastic robust-standard errors clustered within the district in the parentheses. *p<.1, **p<.05, ***p<.01

the time component, we replace the survey fixed effects with a post-NHIS dummy variable and report the estimate in Column (4). After accounting for the characteristics of the women and post-NHIS dummy variable, we still find a strong and statistically significant positive correlation of 1.6 percentage points between the years of NHIS eligibility and NHIS coverage. Since the NHIS coverage rate in the sample is 24.4%, the 1.6 percentage points estimate corresponds to a 6.7% increase in NHIS coverage.

The first stage estimate does not change quantitatively and in precision with or without the women's socio-demographic characteristics accounted for in the models [see Columns (1) and (2)]. It suggests that the characteristics of the women may be uncorrelated with the years of NHIS eligibility. The excluded instrument (years of NHIS eligibility) would be endogenous if districts that initially adopted the NHIS made participation decisions based on healthcare needs or observed and unobserved characteristics of the women. Although we cannot test the exogeneity of our excluded instrument, we perform some diagnostic checks to rule out some of the concerns of possible endogeneity. We report results from linear regressions of the number of months before district adoption of the NHIS on twelve-month medical care use and the observable characteristics of the women in Table 3. The regression, with results reported in the first column, uses only the women surveyed in the pre-NHIS period (i.e., 2003), while we use all the women in the sample and account for survey year fixed effects for the regression whose estimates are reported in the second column. Since only a few of the socio-demographic characteristics are statistically significant, it rules out our concerns that district-staggered roll-outs of the NHIS were pre-determined based on healthcare needs or observable characteristics of the women.

Table 3: Determinants of district NHIS adoption with the number of months before district adoption as the dependent variable

	Linear regression using women from pre-NHIS period	Linear regression using all women
	(1)	(2)
Twelve-month medical care use	-0.537 (0.457)	0.233 (0.254)
Age of woman		
27 – 34	0.234 (0.293)	-0.005 (0.187)
35 – 40	0.211 (0.422)	0.132 (0.225)
41 – 49	0.030 (0.341)	0.129 (0.214)
Currently married	0.196 (0.359)	0.142 (0.237)
Currently pregnant	-0.423 (0.342)	0.083 (0.224)
Births in the last 5 years		
One birth	0.334 (0.296)	0.155 (0.184)
$\geq$ 2 Births	-0.070 (0.435)	-0.440 (0.268)
Number of children		
One child	-0.146 (0.310)	-0.064 (0.174)
Two children	0.258 (0.614)	0.184 (0.332)
$\geq$ Three children	0.023 (0.733)	-0.396 (0.546)
Household wealth index		
2^{nd} Quartile	1.020 (0.695)	0.910 (0.775)
3^{rd} Quartile	2.278** (0.979)	0.099 (1.018)
4^{th} Quartile	0.214 (1.096)	-1.867 (1.163)

Continued on next page

Table 3 – Continued from the previous page

	(1) Linear regression using women from pre-NHIS period	(2) Linear regression using all women
5^{th} Quartile	-2.313* (1.361)	-4.000*** (1.361)
Years of education of woman		
$1-9$	0.676 (0.417)	0.306 (0.344)
$10-12$	1.122** (0.541)	0.482 (0.378)
≥ 13	1.462* (0.760)	0.816* (0.452)
Literate	-0.546 (0.336)	0.088 (0.264)
Employment		
Professionals, tech., mgt., clerks	-0.958* (0.566)	-0.195 (0.338)
Sales & services	-0.239 (0.299)	-0.365 (0.304)
Agric. sector & self-employed	-0.150 (0.656)	-0.496 (0.414)
Manual work	-0.436 (0.582)	-0.918*** (0.338)
Ethnicity		
Akan	-3.422 (2.461)	-2.531 (1.718)
Ga-Dangme, Ewe & Guan	-2.093 (2.493)	-0.869 (1.779)
Mole-Dagbani	-3.025 (2.774)	-0.630 (2.180)
Hausa	-4.775** (2.385)	-1.161 (1.874)
Religion		
Catholic	-0.926 (0.698)	-1.019 (0.732)
Christian	-0.601 (0.693)	-0.225 (0.541)
Muslim	0.545 (1.199)	0.128 (1.389)
Traditional	-0.713 (0.981)	-0.988 (0.881)
Rural residence	1.674 (1.154)	1.415 (0.943)
Survey year fixed effects	N	Y
Number of observations	3,890	15,112

6.1.2 Second Stage Estimates: NHIS and Twelve-Months Medical Care Use

Table 4 presents our naive ordinary least squares (OLS) and IV estimates. The naive OLS estimates after accounting for survey year fixed effects [Column (1)] or post-NHIS dummy [Column (2)] suggest that NHIS coverage is associated with a statistically significant increase in twelve-month medical care use by approximately 13 percentage points. We report the linear IV estimate without accounting for time effect in Column (3), while we included a post-NHIS dummy in the specification in Column (4). The estimate from the specification in Column (4) shows that the women induced by the years of NHIS eligibility to obtain NHIS coverage were 30 percentage points more likely to use medical care. However, the estimate is very imprecise with a large standard error.

Table 4. Naive OLS and second stage estimates: Effects of NHIS on twelve-month medical care use among women using years of NHIS exposure as instrument for insurance participation

	Naive OLS		2SLS	
	(1)	(2)	(3)	(4)
NHIS coverage	0.131*** (0.012)	0.133*** (0.012)	0.246*** (0.079)	0.300 (0.226)
Controls	Y	Y	Y	Y
Post-NHIS dummy	N	Y	N	Y
Survey year fixed effects	Y	N	N	N
Number of observations	15,112	15,112	15,112	15,112

Notes: We include the woman's age, place of resident (rural/urban), marital status of woman, pregnancy status, number of births in the last five years, birth history, wealth index, woman's education, woman's occupation, literacy status of woman, ethnicity, religion, and district fixed effects as the controls in each specification. In Column (3) and (4), we use the years of NHIS exposure as an instrumental variable for the NHIS participation. We report heteroscedastic robust-standard errors clustered within the district in the parentheses. *p<.1, **p<.05, ***p<.01

Our preferred second stage estimate from the linear IV models could be inefficient partly because twelve-month medical care use and NHIS coverage are binary variables. As discussed earlier, the linear IV model may be poorly approximating the marginal effects of highly non-linear models (Altonji et al., 2005a). We address this concern using a bivariate probit model to re-estimate the equations and present the results Table 5. We provide estimates for several specifications due to the flexibility of the bivariate probit models. In Column (1), we exclude the observable characteristics of women and household and time fixed effect from the first and second stage equations. We include the women and household characteristics in the first and second stage equations in the specifications in Columns (2) and (3) but alternate the post-

NHIS dummy and survey year fixed effects in the first and stage equations. The specification in Column (2) includes a post-NHIS dummy variable in both equations. For the specification in the last column, we include the post-NHIS dummy in the first stage equation and survey fixed effects in the second stage equation.

Table 5. Marginal effect estimates of the impact of NHIS on twelve-month medical care use using a bivariate probit model and years of NHIS exposure as an instrument for insurance participation

	(1)	(2)	(3)
NHIS coverage	0.266***	0.320***	0.315***
	(0.070)	(0.096)	(0.112)
Controls	Y/Y	Y/Y	Y/Y
Post-NHIS dummy	N/N	Y/Y	Y/N
Survey year fixed effects	N/N	N/N	N/Y
Number of observations	15,112	15,112	15,112

Notes: We include the woman's age, place of resident (rural/urban), marital status of woman, pregnancy status, number of births in the last five years, birth history, wealth index, woman's education, woman's occupation, literacy status of woman, ethnicity, religion, and district fixed effects as the controls in each specification. We report heteroscedastic robust-standard errors clustered within the district in parentheses. The coefficient of the excluded instrument is statistically significant at 1%, except the specification in Column (2). The notation "N/N" denotes that both the first and second equations of the bivariate model exclude the variable X. *p<.1, **p<.05, ***p<.01

The IV estimates from the bivariate probit model are quantitatively similar to the linear IV estimates but with higher precision and are statistically significant at 1%. Also, they are quantitatively larger than the naive OLS estimates, suggesting that the naive OLS estimates are biased downwards. Focusing on our preferred specification in Column (3), we find that an increase in NHIS coverage induced by the NHIS eligibility increases twelve-month medical care use by approximately 32 percentage points. Since 48% of women in our sample used medical care, the estimate corresponds to a 66% increase in twelve-month medical care use.

Next, we examine how the effect of the NHIS on any twelve-month medical care use differs by household wealth, education, and location of residence from the bivariate probit model and present the results in Table 6. The NHIS coverage statistically significantly increases twelve-month medical care use by approximately 44 percentage points (98%) among women in rural areas [Column (1)]; however, the estimate is not statistically significant for the sample of women from the urban areas [Column (2)]. We find that the NHIS increases twelve-month medical care use among low-wealth household women ($\leq 60^{\text{th}}$ percentile) by 42 percentage points (92%) and high-wealth household women ($> 60^{\text{th}}$ percentile) by 25 percentage points (49%). Finally, we find that the NHIS statistically significantly increases twelve-month medical care use among women with lower years of schooling (≤ 6 years) by 44 percentage points (93%) and those with higher years of education (> 6 years) by 26 percentage point (53%).

One threat to identification is whether growth in the health sector induced participation in the NHIS among women. Hospital openings after the rollout of the NHIS could lead to a surge in NHIS enrollments due to improvement in healthcare access. We include the per $1,000$ person number of hospitals, hospital beds, doctors, or nurses to capture the supply-side effects on medical care use and report the results in Table A3 in the Online Appendix. However, the estimates do not change substantially from our main estimates in Table 5 even after separately or jointly accounting for these supply-side factors. In another robustness checks, we account for other observable characteristics that could influence NHIS enrollment and medical care use decisions. We account for media exposure (radio and television), distance to healthcare centers, and the education and occupation of the women's partners; however, the IV estimates are robust to these additional control variables (Table A4, Online Appendix).

Table 6: Heterogeneity in the effect of the NHIS on twelve-month medical care use using a bivariate probit model and years of NHIS exposure as an instrument for insurance participation

	Location of residence		Wealth of household		Education of woman	
	Rural (1)	Urban (2)	Poorest 60^{th} percentile (3)	Richest 40^{th} percentile (4)	Years of schooling ≤ 6 (5)	Years of schooling > 6 (6)
NHIS coverage	0.440***	0.157	0.421***	0.250**	0.436***	0.256*
	(0.037)	(0.159)	(0.049)	(0.114)	(0.051)	(0.148)
Controls	Y/Y	Y/Y	Y/Y	Y/Y	Y/Y	Y/Y
Post-NHIS dummy	Y/N	Y/N	Y/N	Y/N	Y/N	Y/N
Survey year fixed effects	N/Y	N/Y	N/Y	N/Y	N/Y	N/Y
Number of observations	7,720	7,392	8,975	6,137	6,874	8,238

Notes: We include the woman's age, marital status of woman, pregnancy status, number of births in the last five years, birth history, wealth index, woman's education, woman's occupation, literacy status of woman, ethnicity, religion, and district fixed effects as the controls in each specification. We report heteroscedastic robust-standard errors clustered within the district in parentheses. The notation "Y/N" for a variable X denotes that the first equation of the bivariate probit model includes variable X, whiles the second equation excludes it. *p<.1, **p<.05, ***p<.01

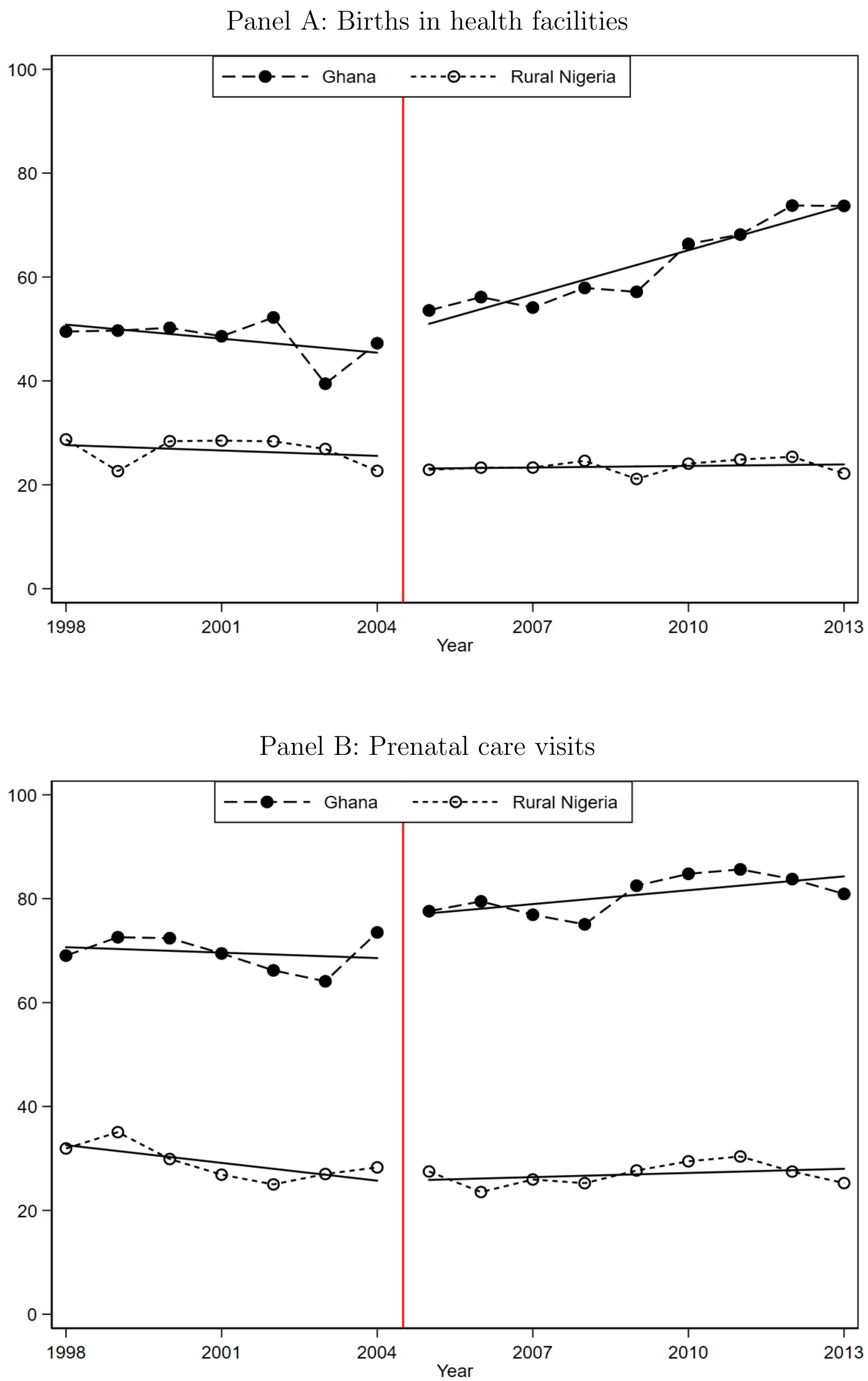
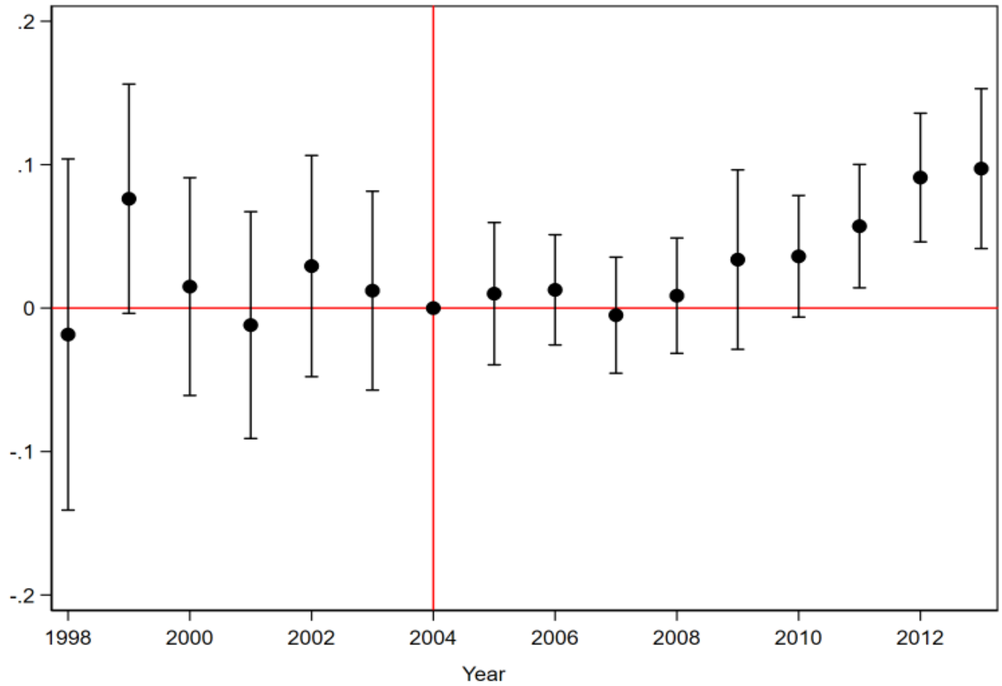
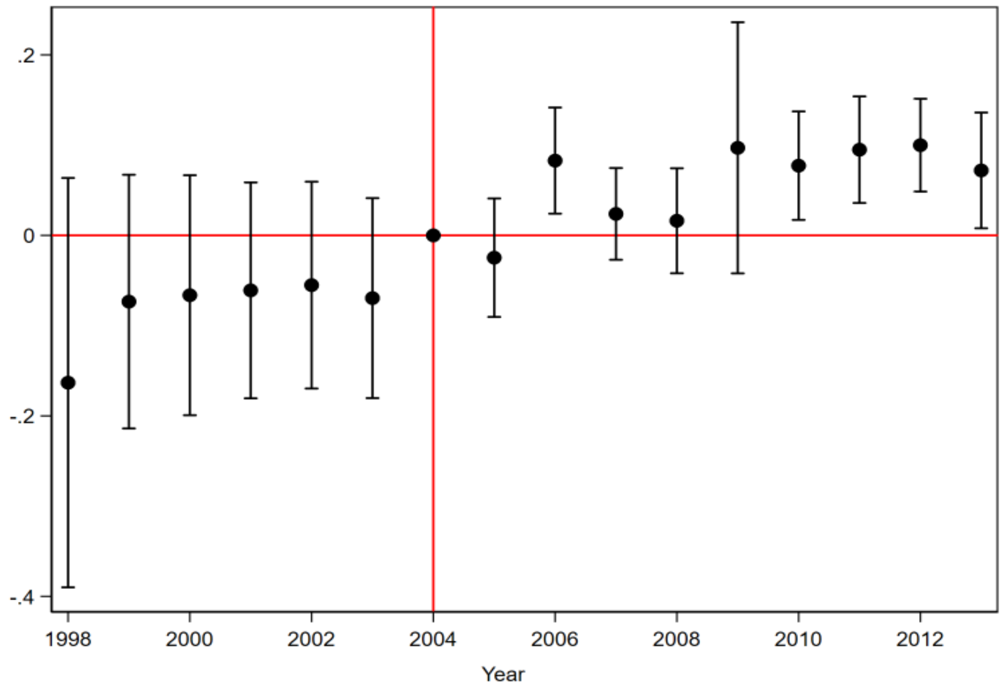


Figure 4: Parallel trends for healthcare use (%) among women in Ghana and Rural Nigeria

Panel A: Births in health facilities



Panel B: Prenatal care visits



Notes: We estimated two separate regression models, with the point estimates (circles) and their 95% confidence intervals (error bars) in each figure. The pre-NHIS period (1998 - 2004) data was used to estimate the pre-NHIS coefficients with 2004 as the reference year. The second regression used all data (1998 - 2013) to generate the post-NHIS estimate, using the pre-NHIS period (1998 - 2004) as the reference point. The regressions accounted for the sex of the child, indicator for twins, birth order, place of residence (rural/urban), household wealth index, mother's age, marital status, education, occupation, literacy status, ethnicity, and religion.

Figure 5: Event study of the effect of NHIS on healthcare utilization

6.2. Effects of the NHIS on Institutional Births and Prenatal Care

We also estimate the effects of the NHIS on births in health facilities and prenatal care visits described in Section 4. We summarize the means, standard deviations, and mean differences in the institutional births and prenatal care visits and the characteristics between the women from Ghana and those from rural Nigeria in Table B1 to B3 in the Online Appendix.

To convincingly estimate the effects of the NHIS on the outcomes using the difference-in-differences strategy, we demonstrate that the outcomes satisfy the parallel trends assumption by plotting trends of health facility visits (Panel A) and prenatal care visits (Panel B) in Figure 4. There were similar trends in the two outcomes between the women in Ghana and rural Nigeria before the implementation of the NHIS; however, there were diverging trends after Ghana implemented the NHIS. In Figure 5, we demonstrate more on the parallel trends for the two outcomes using an event study (see methods in Section C in the Online Appendix) to estimate over time differences in institutional births and prenatal care visits between the women in Ghana and rural Nigeria. Our plots suggest no economically and statistically significant differences between the treatment and comparison groups in the pre-NHIS period for the two outcomes. In the post-NHIS period, we find statistically significant differences in the estimates for the two outcomes in some years.

For the births in health facilities and prenatal-care visits outcomes, we provide estimates from five different specifications (see Tables 7 and 8). While some specifications exclude socio-economic characteristics, others alternate a linear time trend, year of birth fixed effects, and post-NHIS dummy variable. In Panel A, we present our results from the linear probability model (LPM), while Panel B reports the marginal effects from a probit model. For births in health facilities, the estimates from the LPM are quantitatively greater and more precise than the marginal effects from the probit model and shrink when we include observable characteristics and a time variable. For prenatal care visits, the estimates are similar with or without the characteristics of the women, and there are no differences between the estimates from the LPM and a probit model marginal effects.

From on our preferred specification in Column (4), we find that exposure to the NHIS increases the chances of giving births in health facilities by 5.3 percentage points (Table 7). Given that 31% of the children were born in health facilities (Panel A of Table B1), the estimate corresponds to a 16.9% increase. Also, we find that the NHIS increased prenatal care visits by 7.6 percentage points (Table 8) based on our preferred specification in Column (4). Since 36% of the women had prenatal care visits during pregnancy (Panel B of Table B1), the estimate corresponds to a 21% increase. The estimates for births in health facilities (Online Appendix, Table B4) and prenatal care visits (Online Appendix, Table B5) did not change after accounting for additional controls.[17]

The main concern in identifying the parameters in the DID models is whether the women from rural Nigeria are similar to the Ghanaian women in observable and unobservable characteristics. Since Nigeria unsuccessfully implemented NHIS in 1999 and introduced the Formal Sector Social Health Insurance Program in 2005 to provide insurance for federal government and formal private sector employees, some individuals in the comparison group could be treated. Our next robustness check shows the results when we use all women from Nigeria as the comparison group. The estimates reported in Tables B6 and B7 in the Online Appendix are consistently higher than those shown in Tables 7 and 8. They suggest that if the control group included women from urban Nigeria, who could obtain health insurance, our estimates for the effect of the NHIS on births in health facilities and prenatal care visits would be biased upwards.

[17] The additional controls are radio and television exposure, distance to healthcare centers, and the education and occupation of the woman's partner.

Table 7. Difference-in-differences estimates of the effect of NHIS on births in health facilities using women from Rural Nigeria as a comparison group

	(1)	(2)	(3)	(4)	(5)
	Panel A: Coefficients from linear probability models				
Treatment × Post	0.133***	0.114***	0.0918***	0.0838***	0.0627***
	(0.038)	(0.034)	(0.024)	(0.022)	(0.022)
	Panel B: Marginal effects from probit models				
Treatment × Post	0.0974***	0.0746**	0.0648***	0.0525***	0.0290*
	(0.035)	(0.029)	(0.021)	(0.018)	(0.017)
Controls	N	N	Y	Y	Y
Post-NHIS dummy	Y	N	Y	N	Y
Birth year fixed effects	N	Y	N	Y	N
Linear time trend	N	N	N	N	Y
Number of observations	51,080	51,080	51,080	51,080	51,080

Notes: The specifications in Column (3) - (5) include mother, child, and household characteristics that may affect the outcome. They are mother's age at the time of childbirth categorized into four groups, ethnicity, place of resident (rural/urban), religious beliefs, marital status, education and, literacy status, occupation in the survey year, the gender of the child, birth order, and household wealth index. We cluster standard errors at the district and Local Government Agency to account for the overtime correlation in unobserved factors that affect the outcome. The DHS cluster is the same the enumeration area similar to census block (in the U.S.A. context).

Table 8. Difference-in-differences estimates of the effect of NHIS on prenatal care visits using women from Rural Nigeria as a comparison group

	(1)	(2)	(3)	(4)	(5)
	Panel A: Coefficients from linear probability models				
Treatment × Post	0.0717**	0.0675***	0.0834***	0.0743***	0.0732***
	(0.029)	(0.026)	(0.026)	(0.023)	(0.022)
	Panel B: Marginal effects from probit models				
Treatment × Post	0.0734**	0.0680***	0.0878***	0.0759***	0.0716***
	(0.030)	(0.026)	(0.027)	(0.023)	(0.022)
Controls	N	N	Y	Y	Y
Post-NHIS dummy	Y	N	Y	N	Y
Birth year fixed effects	N	Y	N	Y	N
Linear time trend	N	N	N	N	Y
Number of observations	33,464	33,464	33,464	33,464	33,464

Notes: The specifications in Column (3) - (5) include mother, child, and household characteristics that may affect the outcome. They are mother's age at the time of childbirth categorized into four groups, ethnicity, place of resident (rural/urban), religious beliefs, marital status, education and, literacy status, occupation in the survey year, the gender of the child, birth order, and household wealth index. We cluster standard errors at the district and Local Government Agency to account for the overtime correlation in unobserved factors that affect the outcome. The DHS cluster is the same the enumeration area similar to census block (in the U.S.A. context).

Table 9. Difference-in-differences estimates of the effect of the free maternal healthcare policy on births in health facilities using women from Rural Nigeria as a comparison group

	(1)	(2)	(3)	(4)	(5)
	Panel A: Coefficients from linear probability models				
Treatment × Post	0.103***	0.0963***	0.0893***	0.0809***	0.0930***
	(0.034)	(0.031)	(0.023)	(0.022)	(0.020)
	Panel B: Marginal effects from probit models				
Treatment × Post	0.0711**	0.0655**	0.0650***	0.0572***	0.0727***
	(0.031)	(0.029)	(0.019)	(0.017)	(0.015)
Controls	N	N	Y	Y	Y
Post-NHIS dummy	Y	N	Y	N	Y
Birth year fixed effects	N	Y	N	Y	N
Linear time trend	N	N	N	N	Y
Number of observations	51,080	51,080	51,080	51,080	51,080

Notes: The specifications in Column (3) - (5) include mother, child, and household characteristics that may affect the outcome. They are mother's age at the time of childbirth categorized into four groups, ethnicity, place of resident (rural/urban), religious beliefs, marital status, education and, literacy status, occupation in the survey year, the gender of the child, birth order, and household wealth index. We cluster standard errors at the district and Local Government Agency to account for the overtime correlation in unobserved factors that affect the outcome. The DHS cluster is the same the enumeration area similar to census block (in the U.S.A. context).

Table 10. Difference-in-differences estimates of the effect of the free maternal healthcare policy on prenatal care visits using women from Rural Nigeria as a comparison group

	(1)	(2)	(3)	(4)	(5)
	Panel A: Coefficients from linear probability models				
Treatment × Post	0.0371	0.0297	0.0380*	0.0305	0.0381**
	(0.027)	(0.026)	(0.022)	(0.021)	(0.016)
	Panel B: Marginal effects from probit models				
Treatment × Post	0.0437	0.0369	0.0420*	0.0346*	0.0437***
	(0.028)	(0.026)	(0.022)	(0.021)	(0.017)
Controls	N	N	Y	Y	Y
Post-NHIS dummy	Y	N	Y	N	Y
Birth year fixed effects	N	Y	N	Y	N
Linear time trend	N	N	N	N	Y
Number of observations	33,464	33,464	33,464	33,464	33,464

Notes: The specifications in Column (3) - (5) include mother, child, and household characteristics that may affect the outcome. They are mother's age at the time of childbirth categorized into four groups, ethnicity, place of resident (rural/urban), religious beliefs, marital status, education and, literacy status, occupation in the survey year, the gender of the child, birth order, and household wealth index. We cluster standard errors at the district and Local Government Agency to account for the overtime correlation in unobserved factors that affect the outcome. The DHS cluster is the same the enumeration area similar to census block (in the U.S.A. context).

Some mothers in our sample were eligible for free NHIS coverage after the Government of Ghana implemented the free maternal healthcare policy implemented in July 2008. We estimate the effects of the new policy on the two birth-related outcomes and report our results for the births in health facilities and prenatal care visits by separating the effects of the NHIS before (April 2004 to June 2008) and after (July 2008 to May 2013) the free maternal healthcare policy in the same model. The estimates from our preferred specification [Column (4)] show that the free maternal healthcare policy increased births in health facilities by 5.7 percentage points (Table 9) and prenatal care visits by 3.5 percentage points (Table 10). They suggest increases in health facility births by 18% and prenatal care visits by 10% based on average births in health facilities of 31% and prenatal care visits of 36%.

7. Discussion and Conclusion

This study exploits the variation in the district-staggered adoption of Ghana's National Health Insurance Scheme to estimate the causal impact of insurance on healthcare utilization among women aged 15−49 in the Demographic and Health Survey. We jointly model decisions to enroll in the NHIS and twelve-month medical care use, observed only in the survey years (i.e., 2003, 2008, and 2014), using the years of exposure as an instrument for NHIS take-up. The finding is that NHIS coverage increases twelve-month medical care use by about 32 percentage points. We also find that the increase in 12-month medical care use is among only women in rural areas and higher among those in the lower 60th percentile of household wealth distribution and with six or fewer years of schooling. The second set of analyses estimates the intent-to-treat effect of the NHIS on births in health facilities and prenatal care visits using a difference-in-differences framework. We use the date of birth of under five-year-old children to construct samples for mothers' childbirths in health facilities and prenatal care visits for Ghana (treatment group) and rural Nigeria (comparison group) from 1998 – 2013. We find an intent-to-treat estimate of 5.3 percentage points for births in health facilities and 7.6 percentage points for prenatal care visits. The last set of analyses focuses on how the free maternal care policy that provided free NHIIS to pregnant women starting from July 2008 affected births in health facilities and prenatal care visits. Our results show that the add-on policy generates an intent-to-treat estimate of 5.7 percentage points for health facilities and 3.5 percentage points for prenatal care visits.

These results imply that the NHIS increases medical care use among women, which was a significant concern before implementing the health insurance policy. Consequently, we expect improvements in maternal health and a reduction in infant mortalities, which were part of the Millennium Development Goals. Our results also imply reductions in the health disparities between the less advantaged and more advantaged women since the NHIS has higher impacts on women from poor households, rural areas, and with lower years of schooling.

This study provides the most credible causal estimate of the effect of the NHIS on healthcare utilization using the best available data and empirical strategies that overcome methodological challenges in prior studies. We recognize the endogeneity in the insurance program due to the nature of the design of the NHIS and use district-staggered rollouts, a common natural experiment used in causal studies, as an exogenous source of variation to tackle endogeneity in the NHIS participation (Garcia-Mandicó et al., 2021; Strupat and Klohn, 2018) and in other health insurance programs (Cesur et al., 2017; Ater et al., 2017; Liu, 2016; Fink et al., 2013). We demonstrate that the timing of district adoption of the NHIS is uncorrelated with any pre-existing health conditions or the observed characteristics of the women.

Our empirical strategies allowed us to overcome the challenge of making a strong assumption in previous studies that the NHIS participation status of mothers when pregnancy or birth occurred is similar to those observed in the survey year. Given that our study period overlapped the phase-in stage of the NHIS when rollouts were still increasing, we argue that such a strong assumption leads to the misclassification of NHIS participation status among some women. Because the NHIS participation variable takes a zero or one value, measurement errors from misclassification will be non-classical. Importantly, standard error-in-variables methods cannot easily overcome non-classical measurement errors. Therefore, regardless of the source of misclassification, causal identification in the presence of a non-classical measurement error is nontrivial, and failing to account for such issues may lead to biased estimates.

We also overcome concerns of endogenous misreporting in NHIS participation among the women in our sample. The DHS survey questionnaire asked several strategies to validate the NHIS participation responses. We defined our health insurance participation variable to include only the women with verified health insurance cards to mitigate the concerns of endogenous misreporting in the NHIS participation status.

Our estimation techniques allowed us to consistently and efficiently identify the causal impact of our binary endogenous NHIS participation variable on the binary outcomes. Most causal studies on the NHIS use estimation techniques shown to inconsistently estimate the effect of a binary endogenous variable on binary outcomes of interest. We use a bivariate probit estimation technique that produces consistent and efficient estimates, unlike a linear IV model that sometimes gives poor approximations of marginal effects of highly nonlinear models (Lewbel et al., 2012; Altonji et al., 2005a,b; Wooldridge, 2010, pp. 596-597).

A limitation to the study is that we could not account for changes in the aggregate economy that the post-NHIS dummy could not capture when estimating the results for 12-month medical care use observed in the survey years only. However, we suspect economic growth had minimal impacts on healthcare utilization based on similar results from the specifications that accounted for the effects of economic growth using a post-NHIS dummy and year dummies for births in health facilities and prenatal care visits. Another threat to the validity of results for birth-related outcomes is that there could be unmeasured differences (i.e., unobserved heterogeneity) between the women from Ghana and those from rural Nigeria used as a comparison group. Despite these limitations, our study demonstrates that the NHIS effectively increases healthcare utilization and concludes that these findings from the NHIS are in line with programs from developed countries like the U.S. Affordable Care Act (Courtemanche et al., 2017).

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Online Appendix

A. Conceptual Framework

Grossman (1972) provides a basic framework for understanding the demand for health. In his model, people demand "good health" for two reasons. First, in the form of sick-free days, they seek "good health" as a consumption commodity since they become happy when healthy. To produce the "good health," they inherit initial stock of health capital (i.e., their human capital that depreciate with age and increase through investments) and die when their stocks of health fall below certain levels. Second, they demand "good health" viewing it as an investment good that defines the time available for market activities (e.g., formal employment) and non-market activities (e.g., leisure). They can work for wages or engage in home productions during sick-free days. One conclusion from the model is that a ceteris paribus change in the price of a health input changes the "shadow price" of health. Importantly, medical care costs are an input in the "shadow price" of health; therefore, a decrease in medical care costs increases the demand for health investment as a derived demand for health.

The provision of the NHIS in Ghana is similar to reducing the price of health inputs in Grossman's model except for those in perfect health who would spend nothing even without the insurance program. Before the NHIS, the Ghanaian health industry had a limited number of health inputs and high medical costs. There was almost no health insurance in many areas before the NHIS became available. The implementation of the NHIS reduced the expected cost of medical care.[1] Therefore, we expect the majority of Ghanaian residents to enroll in the NHIS. Surprisingly, the annual NHIS participation rate has always been lower than one-half of the Ghanaian population, even after a decade of national coverage (see Figure 1). In part, a theoretical argument for the low take-up is that healthcare utilization may be exhibiting

[1] The cost per bed day and outpatient visit in a hospital were about ₵60,000 and ₵18,000, respectively, in 2005. For more information, see from https://www.who.int/choice/country/gha/cost/en/.

diminishing marginal returns (Folland et al., 2016). However, since healthcare utilization was low before providing the NHIS, we rule out this explanation. We devote the rest of the section to discuss the potential reasons for the low NHIS participation rate.

The household's budget constraint is one reason why some individuals cannot enroll in the NHIS. Although the expected cost of obtaining coverage in the NHIS is lower than the expected expenditure on healthcare utilization, some individuals are unable to enroll due to credit constraints. Given that the majority of the Ghanaian population lives under \$1 every day, the cost of obtaining the NHIS represents a significant expenditure on the budgets of households with low socioeconomic status and large family sizes (Kusi et al., 2015). A survey of households by Kusi et al. (2015) show that about 29% of individuals without NHIS coverage face credit constraints. In our data, about 25% of the women without NHIS coverage in 2014 believes that the NHIS is expensive.

Another reason is that most Ghanaian people patronize the informal healthcare industry, which serves as substitutes or complements to the formal healthcare sector. The government permits the use of traditional, complementary, and alternative medicines as forms of informal healthcare.[2] Evidence shows that about 70% of Ghanaian residents depend on traditional medicine as a primary source of healthcare (World Health Organization, 2001). A recent survey by Gyasi (2015) shows that approximately 87% of their sample uses traditional and alternative medicines.

We also argue that risk-sharing opportunities and social networks serve as alternative insurance for some people in Ghana. Because well-designed insurance programs were initially not available in Ghana, some extended-families, communities, or villages often provided mutual insurance to mitigate impacts of shocks. There is evidence on the existence of risk-sharing

[2] Complimentary or alternative medicine refers to other traditional medicines imported from other countries, but not part of Ghana's traditions. In Ghana, complementary or alternative medicines are highly patronized and usually advertised on the media.

behaviors of group members of organizations and the availability of financial assistance in the event of shock (Goldstein et al., 2002; Fenenga et al., 2015). We suspect that sometimes, joining informal organizations crowd out NHIS coverage due to budget constraints.[3]

Supply-side factors, including access to health facilities and trust in healthcare and NHIS employees, potentially affect participation in the NHIS. Individuals who trust workers in the healthcare industry are more likely to obtain coverage (Fenenga et al., 2015). Kusi et al. (2015) find that most of the individuals in their sample who complained about the poor services from the formal healthcare industry were less likely to participate in the NHIS.[4]

Finally, we argue that religion and culture can affect people's participation in the NHIS. Religious and cultural norms play essential roles in Ghana's healthcare industry. Prayer for healing is a common practice in Ghana, where people seek divine healing from pastors and spiritual superiors. Some people also practice self-medication using their experiences and knowledge in drugs and herbal medicines.[5] A qualitative evidence on the negative relationship between religious and cultural norms and participation in the NHIS exists (Fenny et al., 2016).

B. A Recursive Bivariate Probit Model

An important econometrics issue that several studies overlook but still a debate in the literature is how to estimate binary choice models with endogenous regressors (Lewbel et al., 2012). Our goal is to use an estimation technique that can efficiently and consistently determine the parameters in equations (1) and (2). We would rely on the linear IV [i.e., two-stage least squares (2SLS)] if the outcome in equation (1), Y_{idt}, is continuous, even if the endogenous variable, I_{idt} [i.e., the outcome in equation (2)], is binary. However, since the dependent variable and our

[3] Usually, the expected benefits of becoming a group member of an organization expand beyond just mitigating health shocks even though the evidence is weak in the literature (Fenenga et al., 2015).

[4] Examples of the claims are perceived poor quality of health services, lacked trust in scheme officials, lacked health facilities in their area, experienced negative attitudes from providers, etc.

[5] People visit chemical or drug stores to purchase medications without doctor's prescriptions, except a few, in Ghana.

variable of interest are both binary, we use nonlinear models since the linear IV models cab be bad approximations of highly nonlinear models and lead to inconsistencies marginal effects (Altonji et al., 2005; Lewbel et al., 2012; Angrist and Pischke, 2008, pp. 80).

Below, we show that the linear models may not be good. First, we rewrite the binary choice outcomes in equations (1) and (2) as below:

$$\mathbb{P}(Y_{idt} = 1|\mathbf{X_{idt}}, \mathbf{I_{idt}}, \mathbf{H}) = \boldsymbol{F}(\beta_0 + \beta_1 I_{idt} + \boldsymbol{\Lambda}\mathbf{X_{idt}} + \boldsymbol{\gamma_d} + \boldsymbol{\tau_t}), \tag{1}$$

$$\mathbb{P}(I_{idt} = 1|\mathbf{X_{idt}}, \mathrm{Z}_{dt}, \mathbf{H}) = \boldsymbol{G}(\alpha_0 + \alpha_1 \mathrm{Z_{dt}} + \boldsymbol{\theta}\mathbf{X_{idt}} + \boldsymbol{\lambda_d} + \boldsymbol{\pi_t}), \tag{2}$$

where $\boldsymbol{F}(\bullet)$ and $\boldsymbol{G}(\bullet)$ are nonlinear functions in their arguments, $\mathbf{H}$ represents a vector of the instrument, district and year fixed effect. The 2SLS procedure requires the substitution of the $\boldsymbol{G}$ into the $\boldsymbol{F}$ function to get the conditional expectation function. By substituting equation (7) into (6), we obtain (8) below:

$$\mathbb{P}(Y_{idt} = 1|\mathbf{X_{idt}}, \mathbf{I_{idt}}, \mathbf{H}) = \boldsymbol{F}\{\beta_0 + \beta_1 \boldsymbol{G}(\alpha_0 + \alpha_1 \mathrm{Z_{dt}} + \boldsymbol{\theta}\mathbf{X_{idt}} + \boldsymbol{\lambda_d} + \boldsymbol{\pi_t}) + \boldsymbol{\Lambda}\mathbf{X_{idt}} + \boldsymbol{\gamma_d} + \boldsymbol{\tau_t}\}. \tag{3}$$

The conditional expectation function, $\mathbb{E}$, which we estimate empirically, is given by:

$$\mathbb{E}[Y_{idt} = 1|\mathbf{X_{idt}}, \mathbf{I_{idt}}, \mathbf{H}] = \mathbb{E}[\boldsymbol{F}\{\beta_0 + \beta_1 \boldsymbol{G}(\alpha_0 + \alpha_1 \mathrm{Z_{dt}} + \boldsymbol{\theta}\mathbf{X_{idt}} + \boldsymbol{\lambda_d} + \boldsymbol{\pi_t}) + \boldsymbol{\Lambda}\mathbf{X_{idt}} + \boldsymbol{\gamma_d} + \boldsymbol{\tau_t}\}]. \tag{4}$$

However, because the $\boldsymbol{F}$ and $\boldsymbol{G}$ are nonlinear functions, we cannot pass the expected value through the composite functions, unless we approximate them with linear functions. If they are highly nonlinear, then the linear approximations will be bad. Therefore, using 2SLS can lead to marginal effects that are far from the parameters we are trying to estimate. Another fruitless technique is to use the two-step procedure that mimics the 2SLS. It is tempting to estimate equation (7) to obtain the predicted values (i.e., the predicted values from the first-stage equation) and substitute into the outcome equation in (6) before estimating it. However, with the same reasons why the 2SLS fail, Wooldridge (2010) and Green (1998) argue that substituting first stage fitted values into the outcome equation is inappropriate and cannot produce consistent and efficient estimates.[6]

Although there is no consensus on the best technique to use, most studies in the literature argue for the bivariate probit models. The main weakness is the assumption of joint normality on the error terms, ϵ_{idt} and η_{idt}, as specified below:

$$\begin{pmatrix} \epsilon_{idt} \\ \eta_{idt} \end{pmatrix} \sim \mathbb{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right). \tag{5}$$

The matrices in equation (10) indicate that ϵ_{idt} and η_{idt} are jointly normal, each with mean zero, unit variances, but with an unknown correlation, $\rho \neq 0$.[7] With the assumption of joint normality of the error terms, our $\boldsymbol{G}(\bullet)$ and $\boldsymbol{F}(\bullet)$ functions become $\boldsymbol{\Phi}(\bullet)$, the cumulative normal distribution function. The identification in the bivariate probit framework comes from both the instrument and the functional form restriction. Although we can identify the parameters without the instrument, we include it to allow for a semiparametric identification (Altonji et al., 2005). Unfortunately, there is no econometric theory or formal test to show the relative contribution of the functional form and excluded instrument to the identification of the parameters.

[6]Taking such an approach has been condemned in the literature, and is also regarded as another form of "forbidden regression."

[7]Note that we do not derive the full maximum likelihood functions in this paper. If interested, check Wooldridge (2010, pp. 596 - 597) for the full derivation.

C. Difference-in-Differences Strategy

As indicated earlier, for outcomes that we observe in all years (i.e., 1998−2013), we are unable to use the IV strategy. For the children born in the off-survey years, we do not have their mothers' insurance participation outcomes in utero or at birth. We lose most of them if we drop those whose mothers' NHIS participation outcomes are not available. Since we do not want to assume that the enrollment status of insurance in the survey year and the time of utilization are the same, we use similar individuals from Nigeria as one control group. Combining the children born in Ghana and Nigeria allows us to use difference-in-differences (DID) methodology to estimate the intent-to-treat effect of the NHIS on births in health facilities and prenatal care visits. Consider the baseline specification below:

$$Y_{idct} = \mathbf{1}(\delta_0 + \delta_1 \text{POST}_{dct} + \delta_2(\text{TREAT}_{dc} \times \text{POST}_{dct}) + \mathbf{\Omega X_{idct}} + \boldsymbol{\zeta_d} + \boldsymbol{\Psi_t} + \xi_{idct} > 0), \quad (6)$$

where Y_{idct} represents the outcome of individual i living in district d of country c at year t and POST_{dct} is an indicator for whether district d of country c implemented the NHIS at year t when the outcome was realized. The vector $\mathbf{X_{idct}}$ represents a set of characteristics of individual i living in district d of country c at time t, while ξ_{idct} captures the corresponding unobserved components. The specification also includes a vector of year fixed effect, $\boldsymbol{\Psi_t}$, and district fixed effect, $\boldsymbol{\zeta_d}$, to account for the impacts of time-invariant and district-level characteristics that can cause changes in the outcomes rather than the NHIS. Since only the individuals from districts in Ghana are exposed to the NHIS and no district from Nigeria implemented the NHIS during our study period, we exclude TREAT_{dc} from equation (3) to avoid perfect collinearity.[8]

In equation (3), the parameter of interest is δ_2. Its estimate, $\hat{\delta}_2$, has a causal interpretation

[8] TREAT_{dc} is perfectly collinear with the district fixed effect.

of identifying the intent-to-treat effect of the NHIS on the outcomes if our data satisfy two assumptions. First, we need to ensure that the individuals in our data fulfill the assumption of perfect compliance. (All the individuals must have remained in their assigned group throughout the study period.) If some individuals switched groups, our estimate can be susceptible to non-compliance and be biased.[9] An issue equivalent to the switching of treatment assignment is when the control group receives similar treatment from other programs. In this case, it would be challenging to isolate that program's impact from the causal effect of NHIS that we evaluate. One control group that potentially satisfies this assumption is the under five-year-old children from Nigeria. In our study period, Nigeria's government did not implement any significant health insurance program or policy that affected these children.[10] Even though the federal government of Nigeria established a similar NHIS program in 1999 (Monye, 2006), it was unsuccessful,[11] and it relaunched a new health insurance program called "Formal Sector Social Health Insurance Program (FSSHIP)" in 2005 (Onoka et al., 2014).

Despite the implementation of NHIS and FSSHIP in Nigeria, most mothers of the children in our sample have no insurance coverage. The DHS survey reports indicate that about 98% of women had no health insurance coverage in 2008 and 2013. Also, since most of the population employed in the formal sector live in urban areas (Ibiwoye and Adeleke, 2008), we eliminate the women and their children living in urban areas to use only those residing in rural areas as our control group. By removing the children living in Nigeria's urban areas, we minimize the possibility of including children whose mothers had health insurance coverage in the control group. Using the 2008 and 2013 DHS survey reports, we realize that less than 1% of rural

[9] If some of the individuals in the control group defected to the treatment group, we would overestimate the effect of the NHIS. We would find an underestimated intent-to-treat effect if some individuals also switched from the treatment to the control group.

[10] Nevertheless, if there was any insurance program, we can construct a random sample such that the women in this sub-sample would not be affected significantly.

[11] Anarado (2001) discusses the various reason why the NHIS in Nigeria was unsuccessful. In summary, the author claimed that the NHIS faced implementation issues such as changes in political regimes, poor designs, etc. For example, the NHIS was designed to be compulsory for only a few of the population working in formal sector organizations with ten or more employees and voluntarily for everyone else. Given that a majority of the labor force worked in the agriculture sector, which was predominantly subsistence, the design of the NHIS automatically led to low participation.

Nigeria women had health insurance coverage. Additionally, our data shows that the mothers of only 0.58% of the children in our sample have health insurance coverage.[12]

The second condition for identifying δ_2 in equation (3) is that our data must satisfy the parallel trends assumption. Without the NHIS, any changes in births in health facilities and prenatal care visits that would have taken place in the post-NHIS period would not have varied differentially between the treatment and control groups.

D. Event Studies

While we cannot formally test the parallel trend assumption since we do not observe the counterfactual, we evaluate the chances of satisfying it through event study models. The event study models allow us to interact with our treatment variable, the full set of pre-NHIS year fixed effect. Similar to the approach in Pesko (2018) and Courtemanche et al. (2017), we estimate the parameters using data from the pre-NHIS period and omit the last year as the baseline group. We specify the pre-NHIS period event study model as below:

$$Y_{idct} = \lambda_0 + \lambda_k \sum_{k=1998}^{2003} \mathrm{YEAR}_k \times \mathrm{TREAT}_{dc} + \boldsymbol{\Omega}\mathbf{X_{idct}} + \boldsymbol{\Pi_{cd}} + \boldsymbol{\Psi_t} + \xi_{idct}. \tag{7}$$

In equation (4), we would be concerned if the estimated coefficients, $\hat{\lambda}_k$, for $k = 1998-2003$, are statistically significant and different from zero. However, imprecise estimates or precise zero estimates suggest that there are no observed differences between the treatment and control groups in the pre-NHIS period, conditional on the observable characteristics.

We also take advantage of the event study model to test for differential effects of the NHIS on the outcomes over time. To do this, we use the individuals in the pre-NHIS period (i.e., $1998 - 2004$) as the reference group, and interact with our treatment variable, a full set of

[12] A significant issue that we cannot address with our data is the problem of endogenous migration. If some mothers and their children migrated from urban areas to rural areas after childbirth, we do not observe this information. Additionally, we cannot address women's endogenous migration from rural areas to urban areas but resettle in rural areas after childbirth.

post-NHIS year fixed effect. We specify the post-NHIS period event study model as below:

$$Y_{idct} = \lambda_0 + \lambda_k \sum_{k=2004}^{2013} \text{YEAR}_k \times \text{TREAT}_{dc} + \mathbf{\Omega X_{idct}} + \boldsymbol{\Pi_{cd}} + \boldsymbol{\Psi_t} + \xi_{idct}. \tag{8}$$

In equation (5), the parameters of interest are λ_k, for $k = 2004 - 2013$. We expect their magnitudes and precision to improve as k rises. Achieving such results will provide suggested evidence that the NHIS has differential effects over time.

E. Additional Tables

Table A1. Means and standard deviations (in parenthesis) of the characteristics of women with and without health insurance coverage

	Insured	Uninsured	All women
Currently married	0.52 (0.50)	0.45 (0.50)	0.47 (0.50)
Currently pregnant	0.11 (0.31)	0.08 (0.28)	0.09 (0.28)
Rural residence	0.50 (0.50)	0.52 (0.50)	0.51 (0.50)
Age of woman			
15 − 26	0.40 (0.49)	0.46 (0.50)	0.45 (0.50)
27 − 34	0.29 (0.45)	0.25 (0.43)	0.26 (0.44)
35 − 40	0.18 (0.38)	0.15 (0.36)	0.16 (0.37)
41 − 49	0.17 (0.37)	0.17 (0.38)	0.17 (0.38)
Number of children			
No child	0.40 (0.49)	0.43 (0.50)	0.42 (0.49)
One child	0.36 (0.48)	0.34 (0.47)	0.34 (0.47)
Two children	0.19 (0.39)	0.17 (0.38)	0.18 (0.38)
≥ Three children	0.05 (0.22)	0.06 (0.24)	0.06 (0.23)
Births in the past 5 years			
No birth	0.53 (0.50)	0.61 (0.49)	0.59 (0.49)
One birth	0.31 (0.47)	0.27 (0.44)	0.28 (0.45)
≥ Two births	0.16 (0.37)	0.13 (0.33)	0.13 (0.34)
Household wealth index			
1^{st} Quartile (poorest)	0.21 (0.41)	0.23 (0.42)	0.23 (0.42)
2^{nd} Quartile	0.18 (0.39)	0.18 (0.38)	0.18 (0.38)
3^{rd} Quartile	0.20 (0.40)	0.18 (0.39)	0.19 (0.39)
4^{th} Quartile	0.20 (0.40)	0.20 (0.40)	0.20 (0.40)
5^{th} Quartile (richest)	0.20 (0.40)	0.21 (0.41)	0.21 (0.41)
Years of education of woman			
No education	0.23 (0.42)	0.27 (0.44)	0.26 (0.44)
1 − 9	0.50 (0.50)	0.50 (0.50)	0.50 (0.50)
10 − 12	0.19 (0.39)	0.18 (0.38)	0.18 (0.38)
≥ 13	0.08 (0.27)	0.06 (0.23)	0.06 (0.24)
Literate	0.53 (0.50)	0.48 (0.50)	0.49 (0.50)
Occupation			
Not working	0.25 (0.43)	0.25 (0.43)	0.25 (0.43)
Professionals, tech., mgt., clerks	0.08 (0.26)	0.04 (0.21)	0.05 (0.22)
Sales & services	0.35 (0.48)	0.33 (0.47)	0.34 (0.47)
Agric. sector & self-employed	0.21 (0.40)	0.25 (0.43)	0.24 (0.43)
Manual work	0.12 (0.32)	0.12 (0.33)	0.12 (0.32)
Ethnicity			
Akan	0.41 (0.49)	0.43 (0.50)	0.43 (0.50)
Ga-Dangme, Ewe & Guan	0.21 (0.41)	0.20 (0.40)	0.21 (0.40)
Mole-Dagbani	0.26 (0.44)	0.23 (0.42)	0.23 (0.42)
Hausa	0.10 (0.30)	0.10 (0.30)	0.10 (0.30)
Others	0.02 (0.15)	0.04 (0.20)	0.04 (0.19)
Religion			
Catholic	0.19 (0.39)	0.16 (0.37)	0.17 (0.37)
Christian	0.58 (0.49)	0.60 (0.49)	0.59 (0.49)

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Table A1 – Continued from the previous page

	Insured	Uninsured	All women
Muslim	0.19 (0.39)	0.17 (0.38)	0.18 (0.38)
Traditional	0.02 (0.13)	0.04 (0.19)	0.03 (0.17)
No religion	0.03 (0.16)	0.04 (0.18)	0.03 (0.18)
Year of survey			
2003	0.01 (0.11)	0.34 (0.47)	0.26 (0.44)
2008	0.22 (0.41)	0.21 (0.41)	0.21 (0.41)
2014	0.77 (0.42)	0.46 (0.50)	0.53 (0.50)
Number of Observations	3,683	11,429	15,112

Table A2. Means and standard deviations (in parenthesis) of the characteristics of women (ages $15-49$) with and without twelve month medical care use

	With visits	Without visits	All women
Currently married	0.57 (0.49)	0.37 (0.48)	0.47 (0.50)
Currently pregnant	0.13 (0.34)	0.05 (0.22)	0.09 (0.28)
Rural residence	0.48 (0.50)	0.54 (0.50)	0.51 (0.50)
Age of woman			
$15-26$	0.37 (0.48)	0.52 (0.50)	0.45 (0.50)
$27-34$	0.32 (0.47)	0.20 (0.40)	0.26 (0.44)
$35-40$	0.19 (0.39)	0.14 (0.34)	0.16 (0.37)
$41-49$	0.16 (0.37)	0.18 (0.38)	0.17 (0.38)
Number of children			
No child	0.35 (0.48)	0.49 (0.50)	0.42 (0.49)
One child	0.37 (0.48)	0.31 (0.46)	0.34 (0.47)
Two children	0.21 (0.41)	0.14 (0.35)	0.18 (0.38)
$\geq$ Three children	0.06 (0.25)	0.05 (0.21)	0.06 (0.23)
Births in the past 5 years			
No Birth	0.44 (0.50)	0.72 (0.45)	0.59 (0.49)
One birth	0.36 (0.48)	0.20 (0.40)	0.28 (0.50)
$\geq$ Two births	0.19 (0.40)	0.08 (0.27)	0.13 (0.34)
Household wealth index			
1^{st} Quartile (poorest)	0.22 (0.41)	0.24 (0.43)	0.23 (0.42)
2^{nd} Quartile	0.17 (0.37)	0.19 (0.39)	0.18 (0.38)
3^{rd} Quartile	0.18 (0.39)	0.19 (0.40)	0.19 (0.39)
4^{th} Quartile	0.20 (0.40)	0.19 (0.39)	0.20 (0.40)
5^{th} Quartile (richest)	0.23 (0.42)	0.19 (0.39)	0.21 (0.41)
Years of education of woman			
No education	0.26 (0.44)	0.25 (0.44)	0.26 (0.44)

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Table A2 – Continued from the previous page

	With visits	Without visits	All women
1 − 9	0.47 (0.50)	0.53 (0.50)	0.50 (0.50)
10 − 12	0.19 (0.39)	0.17 (0.38)	0.18 (0.38)
$\geq$ 13+	0.08 (0.27)	0.05 (0.21)	0.06 (0.24)
Literate	0.48 (0.50)	0.50 (0.50)	0.49 (0.50)
Occupation of woman			
Not Working	0.19 (0.39)	0.30 (0.46)	0.25 (0.43)
Professionals, tech., mgt., clerks	0.07 (0.25)	0.04 (0.19)	0.05 (0.22)
Sales & services	0.37 (0.48)	0.31 (0.46)	0.34 (0.47)
Agric. sector & self-employed	0.24 (0.42)	0.25 (0.43)	0.24 (0.43)
Manual work	0.13 (0.34)	0.11 (0.31)	0.12 (0.32)
Ethnicity			
Akan	0.41 (0.49)	0.44 (0.50)	0.43 (0.50)
Ga-Dangme, Ewe & Guan	0.21 (0.41)	0.20 (0.40)	0.21 (0.40)
Mole-Dagbani	0.25 (0.43)	0.22 (0.41)	0.23 (0.42)
Hausa	0.10 (0.30)	0.09 (0.29)	0.10 (0.30)
Others	0.04 (0.18)	0.04 (0.20)	0.04 (0.19)
Religion			
Catholic	0.17 (0.38)	0.17 (0.37)	0.17 (0.37)
Christian	0.59 (0.49)	0.60 (0.49)	0.59 (0.49)
Muslim	0.19 (0.39)	0.16 (0.37)	0.18 (0.38)
Traditional	0.03 (0.17)	0.03 (0.18)	0.03 (0.17)
No religion	0.03 (0.17)	0.04 (0.19)	0.03 (0.18)
Survey year			
2003	0.23 (0.42)	0.29 (0.45)	0.26 (0.44)
2008	0.20 (0.40)	0.22 (0.41)	0.21 (0.41)
2014	0.57 (0.50)	0.50 (0.50)	0.53 (0.50)
Number of observations	7,213	7,899	15,112

Table A3: Robustness to supply-side factors on the impact of NHIS on twelve-month medical care use using bivariate probit model and years of NHIS exposure as an instrument for insurance participation

	(1)	(2)	(3)	(4)	(5)
NHIS coverage	0.276**	0.307***	0.291**	0.314***	0.289***
	(0.1285)	(0.1037)	(0.1224)	(0.0970)	(0.1038)
Number of hospitals (per 1000)	0.559*				0.724*
	(0.3090)				(0.4034)
Number of hospital beds (per 1000)		-0.00294			-0.0193
		(0.0294)			(0.1078)
Number of nurses (per 1000)			0.0726		0.0867
			(0.0695)		(0.0660)
Number of doctors (per 1000)				0.194	0.478
				(0.1367)	(0.4621)
Controls	Y/Y	Y/Y	Y/Y	Y/Y	Y/Y
Post-NHIS dummy	Y/N	Y/N	Y/N	Y/N	Y/N
Survey year fixed effects	N/Y	N/Y	N/Y	N/Y	N/Y
Number of observations	15,112	15,112	15,112	15,112	15,112

Notes: We include the woman's age, place of resident (rural/urban), marital status of woman, pregnancy status, number of births in the last five years, birth history, wealth index, woman's education, woman's occupation, literacy status of woman, ethnicity, religion, and district fixed effects as the controls in each specification. Additionally, we include the number of hospital beds to capture supply-side effects. We report heteroscedastic robust-standard errors clustered within the district in the parentheses. The notation "N/N" for a variable X denotes that both the first and second equations of the bivariate model exclude the variable X. *p<.1, **p<.05, ***p<.01

Table A4: Robustness to additional controls on the impact of NHIS on twelve-month medical care use using bivariate probit model and years of NHIS exposure as an instrument for insurance participation

	(1)	(2)	(3)	(4)
NHIS coverage	0.270***	0.314***	0.302***	0.309***
	(0.066)	(0.091)	(0.111)	(0.104)
Controls	Y/Y	Y/Y	Y/Y	Y/Y
Post-NHIS dummy	N/N	N/N	Y/Y	Y/N
Survey year fixed effects	N/N	Y/Y	N/N	N/Y
Number of observations	15,112	15,112	15,112	15,112

Notes: We include the woman's age, place of resident (rural/urban), marital status of woman, pregnancy status, number of births in the last five years, birth history, wealth index, woman's education, woman's occupation, literacy status of woman, ethnicity, religion, and district fixed effects as the controls in each specification. Additionally, we include dummies for frequent television viewer and radio listener and education and occupation of the mother's partner at the time of the survey. We report heteroscedastic robust-standard errors clustered within the district in the parentheses. The notation "N/N" for a variable X denotes that both the first and second equations of the bivariate model exclude the variable X. *p<.1, **p<.05, ***p<.01

Table B1. Means and standard deviations (in parenthesis) of births in health facilities and prenatal care visits for the treatment, comparison group & the full sample

Panel A: Births in health facilities

	Treatment group		
	Pre-NHIS	Post-NHIS	All women
Treatment group	0.48 (0.50)	0.65 (0.48)	0.58 (0.49)
Number of observations	3,814	5,161	8,975
	Comparison group		
	Pre-NHIS	Post-NHIS	All women
Comparison group	0.27 (0.44)	0.24 (0.43)	0.24 (0.43)
Number of observations	4,145	37,960	42,105
	Full sample		
	Pre-NHIS	Post-NHIS	All women
All women	0.37 (0.48)	0.29 (0.45)	0.31 (0.46)
Number of observations	7,959	43,121	51,080

Panel B: Prenatal care visits

	Treatment group		
	Pre-NHIS	Post-NHIS	Total
Treatment group	0.69 (0.46)	0.81 (0.39)	0.76 (0.43)
Number of observations	2,574	3,611	6,185
	Comparison group		
	Pre-NHIS	Post-NHIS	Total
Comparison group	0.27 (0.45)	0.27 (0.45)	0.27 (0.45)
Number of observations	2,452	24,827	27,279
	Full sample		
	Pre-NHIS	Post-NHIS	Total
All Children	0.49 (0.50)	0.34 (0.47)	0.36 (0.48)
Number of observations	5,026	28,438	33,464

Table B2. Means and standard deviations (in parenthesis) of household and women characteristics by treatment group, comparison group & all women in births in health facilities sample

	Treatment group	Comparison group	All women
Post-NHIS period	0.58 (0.49)	0.90 (0.30)	0.84 (0.36)
Treatment group			0.18 (0.38)
Treatment × Post	0.58 (0.49)		0.10 (0.30)
Characteristics of child			
Male	0.51 (0.50)	0.51 (0.50)	0.51 (0.50)
Twin	0.02 (0.13)	0.08 (0.13)	0.02 (0.13)
Birth order			
First	0.23 (0.42)	0.18 (0.38)	0.19 (0.39)
Second	0.20 (0.40)	0.16 (0.37)	0.17 (0.37)
Third	0.16 (0.37)	0.15 (0.35)	0.15 (0.36)
Fourth	0.13 (0.34)	0.13 (0.33)	0.13 (0.34)
$\geq$ Fifth	0.28 (0.45)	0.39 (0.49)	0.37 (0.48)
Household characteristics			
Rural residence	0.65 (0.48)		0.94 (0.24)
Household wealth index			
1st Quartile (poorest)	0.33 (0.47)	0.32 (0.47)	0.32 (0.47)
2nd Quartile	0.22 (0.42)	0.30 (0.46)	0.29 (0.45)
3rd Quartile	0.17 (0.38)	0.21 (0.41)	0.20 (0.40)
4th Quartile	0.15 (0.36)	0.12 (0.33)	0.13 (0.33)
5th Quartile (richest)	0.13 (0.33)	0.04 (0.20)	0.06 (0.23)
Currently married	0.74 (0.44)	0.93 (0.25)	0.90 (0.30)
Mother's Age			
$15-26$	0.32 (0.47)	0.42 (0.49)	0.40 (0.49)
$27-34$	0.42 (0.49)	0.37 (0.48)	0.38 (0.49)
$35-40$	0.21 (0.41)	0.19 (0.39)	0.19 (0.39)
$41-49$	0.09 (0.29)	0.07 (0.25)	0.07 (0.26)
Years of education of woman			
No education	0.41 (0.49)	0.57 (0.50)	0.55 (0.50)
$1-9$	0.46 (0.50)	0.29 (0.46)	0.32 (0.47)
$10-12$	0.10 (0.30)	0.11 (0.32)	0.11 (0.31)
≥ 13	0.03 (0.17)	0.02 (0.14)	0.02 (0.15)
Literate	0.27 (0.45)	0.29 (0.45)	0.29 (0.45)
Occupation of woman			
Not working	0.13 (0.34)	0.32 (0.47)	0.29 (0.45)
Manual work	0.12 (0.33)	0.10 (0.30)	0.11 (0.31)
Professionals, tech., mgt., clerks	0.03 (0.17)	0.02 (0.13)	0.02 (0.14)
Sales & services	0.40 (0.49)	0.20 (0.40)	0.24 (0.43)
Agric. sector & self-employed	0.32 (0.47)	0.35 (0.48)	0.35 (0.48)
Ethnicity			
Hausa	0.13 (0.34)	0.32 (0.47)	0.29 (0.45)
Ghana: Akan	0.38 (0.49)		0.07 (0.25)
Ghana: Ga-Dangme, Ewe & Guan	0.18 (0.39)		0.03 (0.18)
Ghana: Mole-Dagbani	0.26 (0.44)		0.05 (0.21)
Ghana: Others	0.05 (0.21)		0.01 (0.09)
Nigeria: Fulani		0.11 (0.31)	0.09 (0.29)

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Table B2 – Continued from the previous page

	Treatment group	Comparison group	All women
Nigeria: Igbo		0.07 (0.25)	0.05 (0.23)
Nigeria: Yoruba		0.06 (0.23)	0.05 (0.21)
Nigeria: Others 1		0.14 (0.34)	0.11 (0.32)
Nigeria: Others 2		0.33 (0.47)	0.27 (0.45)
Religion			
No religion	0.06 (0.24)		0.01 (0.10)
Catholic	0.15 (0.35)	0.08 (0.26)	0.09 (0.28)
Christian	0.53 (0.50)	0.28 (0.45)	0.32 (0.47)
Muslim	0.20 (0.40)	0.61 (0.49)	0.54 (0.50)
Traditional	0.06 (0.24)	0.02 (0.13)	0.03 (0.16)
Survey year			
2003	0.36 (0.48)	0.08 (0.27)	0.13 (0.34)
2008	0.25 (0.44)	0.50 (0.50)	0.42 (0.49)
2013		0.47 (0.50)	0.39 (0.49)
2014	0.39 (0.49)		0.07 (0.25)
Observations	8,975	42,105	51,080

Table B3. Means and standard deviations (in parenthesis) of household and women characteristics by treatment group, comparison group & all women in births in prenatal care visits sample

	Treatment group	Comparison group	All women
Post-NHIS period	0.58 (0.49)	0.91 (0.29)	0.85 (0.36)
Treatment group			0.19 (0.39)
Treatment × Post	0.58 (0.49)		0.11 (0.31)
Characteristics of child			
Male	0.51 (0.50)	0.51 (0.50)	0.51 (0.50)
Twin	0.02 (0.13)	0.02 (0.13)	0.02 (0.13)
Birth order			
First	0.22 (0.41)	0.17 (0.37)	0.18 (0.38)
Second	0.19 (0.40)	0.15 (0.36)	0.16 (0.37)
Third	0.16 (0.37)	0.14 (0.35)	0.14 (0.35)
Fourth	0.14 (0.34)	0.13 (0.33)	0.13 (0.34)
$\geq$ Fifth	0.29 (0.46)	0.41 (0.49)	0.39 (0.49)
Household characteristics			
Rural Residence	0.63 (0.48)		0.93 (0.25)
Household wealth index			
1st Quartile (poorest)	0.30 (0.46)	0.32 (0.47)	0.32 (0.47)

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Table B3 – Continued from the previous page

	Treatment group	Comparison group	All women
2^{nd} Quartile	0.22 (0.41)	0.30 (0.46)	0.28 (0.45)
3^{rd} Quartile	0.18 (0.39)	0.21 (0.41)	0.21 (0.41)
4^{th} Quartile	0.17 (0.37)	0.12 (0.33)	0.13 (0.34)
5^{th} Quartile (richest)	0.14 (0.34)	0.05 (0.21)	0.06 (0.24)
Currently married	0.73 (0.45)	0.92 (0.27)	0.89 (0.32)
Mother's Age			
$15-26$	0.33 (0.47)	0.42 (0.49)	0.40 (0.49)
$27-34$	0.40 (0.49)	0.35 (0.48)	0.36 (0.48)
$35-40$	0.21 (0.41)	0.19 (0.40)	0.20 (0.40)
$41-49$	0.11 (0.31)	0.08 (0.26)	0.08 (0.27)
Years of education of woman			
No education	0.39 (0.49)	0.56 (0.50)	0.53 (0.50)
$1-9$	0.47 (0.50)	0.29 (0.46)	0.33 (0.47)
$10-12$	0.11 (0.31)	0.12 (0.33)	0.12 (0.32)
≥ 13	0.03 (0.18)	0.02 (0.15)	0.03 (0.16)
Literate	0.29 (0.46)	0.30 (0.46)	0.30 (0.46)
Occupation of woman			
Not working	0.13 (0.33)	0.32 (0.47)	0.28 (0.45)
Manual work	0.13 (0.33)	0.10 (0.30)	0.11 (0.31)
Professionals, tech., mgt., clerks	0.03 (0.17)	0.02 (0.13)	0.02 (0.14)
Sales & services	0.34 (0.47)	0.36 (0.48)	0.35 (0.48)
Agric. sector & self-employed	0.38 (0.49)	0.20 (0.40)	0.24 (0.42)
Ethnicity			
Hausa	0.12 (0.33)	0.31 (0.46)	0.28 (0.45)
Ghana: Akan	0.39 (0.49)		0.07 (0.26)
Ghana: Ga-Dangme, Ewe & Guan	0.19 (0.39)		0.04 (0.18)
Ghana: Mole-Dagbani	0.25 (0.44)		0.05 (0.21)
Ghana: Others	0.05 (0.21)		0.01 (0.09)
Nigeria: Fulani		0.11 (0.31)	0.09 (0.28)
Nigeria: Igbo		0.07 (0.25)	0.06 (0.23)
Nigeria: Yoruba		0.06 (0.24)	0.05 (0.22)
Nigeria: Others 1		0.14 (0.34)	0.11 (0.31)
Nigeria: Others 2		0.34 (0.47)	0.27 (0.45)
Religion			
No religion	0.05 (0.23)		0.01 (0.10)
Catholic	0.15 (0.34)	0.079 (0.27)	0.09 (0.29)
Christian	0.54 (0.50)	0.29 (0.45)	0.33 (0.47)
Muslim	0.20 (0.40)	0.59 (0.49)	0.52 (0.50)
Traditional	0.05 (0.23)	0.02 (0.13)	0.02 (0.15)
Survey year			
2003	0.37 (0.48)	0.08 (0.28)	0.14 (0.34)
2008	0.27 (0.45)	0.45 (0.50)	0.42 (0.49)
2013		0.47 (0.50)	0.38 (0.49)
2014	0.36 (0.48)		0.07 (0.25)
Number of observations	6,185	27,279	33,646

Table B4 Robustness to additional controls on the difference-in-differences estimates of NHIS on births in health facilities using women from Rural Nigeria as a comparison group

	(1)	(2)	(3)	(4)	(5)
	Panel A: Coefficients from Linear Probability Models				
Treatment × Post	0.095***	0.088***	0.086***	0.083***	0.062***
	(0.024)	(0.025)	(0.021)	(0.022)	(0.021)
	Panel B: Marginal Effects from Probit Models				
Treatment × Post	0.054***	0.047**	0.054***	0.051***	0.028*
	(0.019)	(0.020)	(0.017)	(0.018)	(0.017)
Controls	N	N	Y	Y	Y
Post-NHIS dummy	Y	N	Y	N	Y
Birth year fixed effects	N	Y	N	Y	N
Linear time trend	N	N	N	N	Y
Number of observations	46,857	46,857	46,857	46,857	46,857

Notes: The specifications in Column (3) - (5) include mother, child, and household characteristics that may affect the outcome. They are mother's age at the time of childbirth categorized into four groups, ethnicity, place of resident (rural/urban), religious beliefs, marital status, education and, literacy status, occupation in the survey year, the gender of the child, birth order, and household wealth index. Some of the models also include year of birth fixed effects to account for changes in the national trends in the healthcare sector, income, and other factors that may increase growth. We cluster standard errors at the district and Local Government Agency to account for the overtime correlation in unobserved factors that affect the outcome. The DHS cluster is the same the enumeration area similar to census block (in the U.S.A. context).

Table B5 Robustness to additional controls on the difference-in-differences estimates of NHIS on prenatal care visits using women from Rural Nigeria as a comparison group

	(1)	(2)	(3)	(4)	(5)
	Panel A: Coefficients from Linear Probability Models				
Treatment × Post	0.047**	0.039*	0.063***	0.056**	0.057***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
	Panel B: Marginal Effects from Probit Models				
Treatment × Post	0.045**	0.037*	0.061***	0.054**	0.054**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)
Controls	N	N	Y	Y	Y
Post-NHIS dummy	Y	N	Y	N	Y
Birth year fixed effects	N	Y	N	Y	N
Linear time trend	N	N	N	N	Y
Number of observations	33,401	33,401	33,401	33,401	33,401

Notes: The specifications in Column (3) - (5) include mother, child, and household characteristics that may affect the outcome. They are mother's age at the time of childbirth categorized into four groups, ethnicity, place of resident (rural/urban), religious beliefs, marital status, education and, literacy status, occupation in the survey year, the gender of the child, birth order, and household wealth index. Some of the models also include year of birth fixed effects to account for changes in the national trends in the healthcare sector, income, and other factors that may increase growth. We cluster standard errors at the district and Local Government Agency to account for the overtime correlation in unobserved factors that affect the outcome. The DHS cluster is the same the enumeration area similar to census block (in the U.S.A. context).

Table B6 Difference-in-differences estimates of the effect of NHIS on births in health facilities using women from Nigeria as a comparison group

	(1)	(2)	(3)	(4)	(5)
	Panel A: Coefficients from Linear Probability Models				
Treatment × Post	0.116***	0.101***	0.105***	0.102***	0.084***
	(0.033)	(0.033)	(0.021)	(0.022)	(0.022)
	Panel B: Marginal effects from probit models				
Treatment × Post	0.088***	0.074**	0.074***	0.071***	0.052***
	(0.028)	(0.029)	(0.017)	(0.018)	(0.017)
Controls	N	N	Y	Y	Y
Post-NHIS dummy	Y	N	Y	N	Y
Birth year fixed effects	N	Y	N	Y	N
Linear time trend	N	N	N	N	Y
Number of observations	65,032	65,032	65,032	65,032	65,032

Notes: The specifications in Column (3) - (5) include mother, child, and household characteristics that may affect the outcome. They are mother's age at the time of childbirth categorized into four groups, ethnicity, place of resident (rural/urban), religious beliefs, marital status, education and, literacy status, occupation in the survey year, the gender of the child, birth order, and household wealth index. Some of the models also include year of birth fixed effects to account for changes in the national trends in the healthcare sector, income, and other factors that may increase growth. We cluster standard errors at the district and Local Government Agency to account for the overtime correlation in unobserved factors that affect the outcome. The DHS cluster is the same the enumeration area similar to census block (in the U.S.A. context).

Table B7 Difference-in-differences estimates of the effect of NHIS on prenatal care visits using women from Nigeria as a comparison group

	(1)	(2)	(3)	(4)	(5)
	Panel A: Coefficients from Linear Probability Models				
Treatment × Post	0.076***	0.071***	0.083***	0.082***	0.081***
	(0.023)	(0.023)	(0.021)	(0.021)	(0.021)
	Panel B: Marginal effects from probit models				
Treatment × Post	0.084***	0.079***	0.090***	0.089***	0.086***
	(0.025)	(0.025)	(0.022)	(0.022)	(0.022)
Controls	N	N	Y	Y	Y
Post-NHIS dummy	Y	N	Y	N	Y
Birth year fixed effects	N	Y	N	Y	N
Linear time trend	N	N	N	N	Y
Number of observations	46,271	46,271	46,271	46,271	46,271

Notes: The specifications in Column (3) - (5) include mother, child, and household characteristics that may affect the outcome. They are mother's age at the time of childbirth categorized into four groups, ethnicity, place of resident (rural/urban), religious beliefs, marital status, education and, literacy status, occupation in the survey year, the gender of the child, birth order, and household wealth index. Some of the models also include year of birth fixed effects to account for changes in the national trends in the healthcare sector, income, and other factors that may increase growth. We cluster standard errors at the district and Local Government Agency to account for the overtime correlation in unobserved factors that affect the outcome. The DHS cluster is the same the enumeration area similar to census block (in the U.S.A. context).

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