The Impact of Community Based Health Financing on Healthcare Behavior and Household Wealth in Kenya:
A Difference-in-Differences Analysis

Prepared by:
Ankur Singh Chawla
MPP Candidate
The Sanford School of Public Policy
Duke University

Project Advisor:
Elizabeth Frankenberg, Ph.D.
The Sanford School of Public Policy
Duke University

Committee Member:
Pope McCorkle III, J.D.
The Sanford School of Public Policy
Duke University

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Abstract

Community based health insurance financing schemes (CBHI/Fs) are a form of localized health insurance that is becoming increasingly popular in developing countries. CBHI schemes use a risk pooling model to provide communities with micro-insurance packages for healthcare. However, empirical evidence on the impact of CBHIs is sparse and CBHI programs have not been systematically scaled up in developing country contexts. I examine a CBHI program in Kenya run by Afya Yetu Initiative, a local NGO with some support from international aid organizations. I use quasi-experimental techniques to run a difference-in-differences analyses on various health behaviors and household wealth outcomes. I find that people who live near an AYI CBHF scheme (within 5 kilometers) are more likely to be enrolled in health insurance schemes and use contraceptives, with a more pronounced impact on males and a smaller impact on the poor. I also find that mothers – and especially poor mothers – also see positive health behaviors from living in proximity to an AYI CBHF. Finally, I find no impact of CBHF schemes on household wealth.

I. Introduction

Barriers to health financing in Kenya exclude as many as 35 million, or 80% of the population of Kenya, from quality healthcare coverage (World Bank, 2014). Despite a broad government mandate for the National Hospital Insurance Fund (NHIF) to cover Kenyans over the age of 18, only a minority of people are enrolled in NHIF health insurance due to inflated user fees and lack of penetration in the informal sector (Chuma & Ogunku, 2011). The consequences are daunting for poor and vulnerable Kenyans: only 44% of births in Kenya are delivered by a skilled healthcare provider, and maternal death is the leading cause of death in women of childbearing age (15%) (DSW, 2011). The risk to vulnerable populations is growing, with a rapid annual population growth of 2.8% (or 1 million new births per year). The Government of Kenya's health expenditures are highly leveraged, with 93% of annual expenditures going to recurring costs (Amendah, 2015).

In this report, I will look at a health financing option that is still somewhat unproven in the East African health context. I examine the impact of risk pooling mechanisms in Kenya, and specifically, the use of Community-Based Health Insurance schemes (CBHIs) in financing healthcare for the poor. CBHIs are risk-pooling mechanisms among small communities in the informal economy, often set up by NGOs. The Afya Yetu Initiative (AYI) comprises the largest group of CBHIs in Kenya. AYI launches and manages 86 CBHIs and 35,000 beneficiaries in three neighboring counties: Nyeri, Kirinyaga, and Muranga. My report will test the following hypothesis: *AYI CBHI schemes create access to healthcare coverage for Kenyans in the form of increased health service utilization or reduced out-of-pocket payments.* If CBHI schemes can be proven to be a successful instrument for creating access to healthcare services, then they can become a powerful and cost-effective form of alternative health financing. This has ramifications for international donor agencies, NGOs, and the Government of Kenya with regards to resource mobilization for healthcare moving forward.

II. Problem Statement

Kenya is a major recipient of US foreign assistance, especially for health-related services. In FY 2016, foreign assistance is set at $630 million, with $542 million dedicated towards health. Within the health sector, the areas of intervention include: strengthening health systems, HIV/AIDS, infectious diseases, maternal and child health, family planning.

In 1994, the Government of Kenya (GoK) approved the Kenya Health Policy Framework, which outlined the long-term goals for Kenya's healthcare sector. The goals aimed to increase efficient use of resources, update outdated systems and laws, and account for rapid population growth and increasing concentration of diseases in Kenya (Muga, 2005: 13).

In response to this new long-term strategy, the Ministry of Health developed the National Health Sector Strategic Plan in 1999, which aimed to put these policy objectives into action. However, five years after its implementation, an external review found that the plan largely failed to improve healthcare for Kenyans. Some reasons included a lack of a proper legislative framework and inadequate coordination among key institutions. Given the public sector's inability to implement necessary health care reforms, the private sector has increased its involvement in delivering healthcare services (16).

The rapid urbanization and population growth Kenya has experienced over the last 20 years has outstripped the public sector's ability to provide vital healthcare services for Kenyans. This gap has been largely filled by the private health sector (Bakinbinga, et al., 2014). In 1992, the private sector owned 47% of the health facilities in Kenya, and by 2006, it owned 59% (Barnes, 2010: 8). The healthcare providers in the private health sector are divided into two groups. One group contains large, modern hospitals and clinics that primarily service middle-to-upper income Kenyans. These are concentrated in Kenya's three largest cities: Nairobi, Kisumu and Mombasa. The other group is full of small-scale providers that service lower and lower middle income Kenyans. Many of the small-scale providers are hampered by inadequate funding and provide services of inconsistent quality. As such, the private sector has been fully unable to bridge the gap between rural Kenyans and access to healthcare.

III. Literature Review: Healthcare Financing

Stakeholders in Kenya's Healthcare Sector

USAID has been instrumental in restructuring Kenya's health care sector. USAID's New Partnerships Initiative is aimed at supporting the development of NGOs and other development partners in poor countries. Kenya is one of the seven "leading edge missions" under this initiative (Hearn, 2011). USAID funding has encouraged the development of the private health sector over the public. Some say that USAID's domination over Kenya's health sector is "societal engineering being undertaken by western donors" (3).

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Reasons for the growth of the private sector in the healthcare market include: "lack of adequate and quality public healthcare services; the introduction of user fees in public facilities; and health sector reforms in the 1980s and 1990s that relaxed licensing and regulation of private health care providers and allowed public sector personnel to work in private practice." (8)

The GoK has recognized the importance of the private sector in the health arena. In their Vision 2030 plan, they included plans for growing the private sector's presence in the health sector (11). In 2011, closely following the implementation of the new 2010 Constitution, the government passed the Kenyan Public-Private Partnership Bill, which made it easier for the private sector to provide public services (Muga, et al., 2005).

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Health Data Framework

Major players in Kenya's healthcare sector, including GoK, NGOs, and private institutions, have recently invested in strengthening data collection tools and creating a framework for analysis of health data (WHO, 2016). High-quality data collection, combined with better health information system design, can help stakeholders in the healthcare system identify priorities and needs. As such, the Kenya Ministry of Health launched the Kenya Health Data Collaborative (HDC) with the assistance of global health partners in 2016. The HDC held a meeting in May 2016, entitled the One Monitoring & Evaluation Framework for the Health Sector Conference.

As a result of the conference this past May, the HDC published a report on integrating health information systems into a common, standardized M&E framework (WHO, 2016). The objectives of HDC include (a) enhancing country level capacity to conduct M&E, (b) improving efficiency and alignment of investments in health data systems through coordination, (c) increasing impact of global public goods on health data systems through increased learning and engagement. To move towards these objectives, HDC stakeholders agreed upon a specific scope for a M&E framework in Kenya. Key components of this framework include the establishment of a common data architecture, enhance sharing of data, and improving technical accountability in the health sector.

Traditional sources of healthcare financing

Healthcare financing comes from three sources: out-of-pocket expenditures, government expenditures, and donor expenditures (Chuma & Ogunku, 2011). Donor funding has increased from 8% in 1994 to 40.6% of total healthcare expenditures in 2009, but most this funding went to HIV/AIDS programs. Health insurance coverage, which includes both voluntary and mandatory schemes, is critically lacking: only 10% of Kenyans have health insurance. There is a wide urban/rural and rich/poor gap in insurance coverage (5).

The primary source of health insurance is the National Health Insurance Fund (NHIF). It is a source of mandatory insurance for those working in the formal sectors. NHIF was set up for progressive contributions (i.e. the rich pay a higher share), but due to inflation and a lack of reform, this progressivity no longer exists (5). Private health insurance has been growing, but it is still limited to rich, urban Kenyans. However, these insurance providers often cannot cover people with chronic conditions (i.e. HIV/AIDS) with affordable premiums. Additionally, private health insurance beneficiaries can submit their payments as a tax relief, which essentially means the poor are subsidizing health care for the rich (6).

All Kenyans are entitled to healthcare services at public hospitals, provided they can pay the user fees. User fees have been a major disruption to poor Kenyans seeking health services, but the government subsidizes the cost of primary healthcare services with its revenue capacity. While user fees in dispensaries and health centers were eliminated in 2004 (replaced with a small flat fee), Chuma & Ogunku found that there have been major delays in these clinics receiving their funding. In 2008/9, clinics only received 36.7% of their budget allocation, which severely limits them from providing primary care services (8).

Alternative financing mechanism: Community-Based Health Insurance

The Government of Kenya (GoK) is limited in its ability to increase spending on healthcare provision. In the past ten years, real financing allocations by the public sector have either declined or remained the same (Okech & Gitahi, 184). More troubling, recurrent expenditures (fixed costs) have been higher than investment expenditures (which could increase coverage). There has been no increase in health system resources: OOP as a percentage of GDP and government spending has been stagnant (185).

Risk-pooling is a major financing alternative suggested by Okech & Gitahi. In this scenario, community members contribute micro payments to a pool that any of them can draw on if they require healthcare services. This is specifically designed to reduce incidence of financial catastrophe and impoverishment for vulnerable Kenyans (because OOP payments and user fees have led to high incidence of these two things) (188). To implement risk pooling, institutions identify the sub-populations among the poor with an ability and willingness to pay for pooled insurance. The government could also subsidize this pool through cross-subsidized or donor-subsidized insurance premiums.

However, there is little evidence about the success of CBHIs in the East African context, and the empirical literature from around the world suggests that impact is unclear. Furthermore, CBHI case studies have pointed out that schemes also have substantial sustainability problems (Ranson et al., 2007; Carrin, 2003; Cohen, 2006). Ownership and management over CBHI schemes are common. Often, CBHIs are in remote areas with little access to medical services. Depending on scheme design, incentives are frequently lacking for members to continue self-financing the program. As with many international development and global health programs, the design and execution is the biggest factor for project sustainability.

One CBHI scheme in Kenya's central province, the Afya Yetu Initiative (AYI), has experienced sustained success with launching and managing rural CBHIs. In the next section, I will discuss the design, stakeholders, and key measures of success for AYI's CBHIs schemes.

IV. Case Study: Afya Yetu Initiative (AYI)

AYI began in 2006 as a successor to an earlier CBHI initiative in Kenya's central province (Oyaya et al, 2015: 11). In 2009, it launched Phase 1 of a six-year plan to launch CBHI schemes in Nyeri, Kirinyaga, and Muranga counties.[1] Phase 1 ran from 2009 to 2011, during which time it launched 29 schemes. Phase 2 ran from 2012 to 2015, which brought the total number of schemes to 86. The Kenya Community Based Health Financing Association (KCBHFA), which coordinates communication and assistance between CBHI organizations throughout the country, reported that AYI is the largest group of CBHIs in Kenya (Koven et al., 2014: 17). But perhaps more importantly, none of their CBHI schemes failed over the six years (interview with AYI). Below, I examine the organizational model of AYI's CBHIs to better understand the mechanisms that strengthen their sustainability and resiliency.

Program Design

Unlike CBHI schemes in theory, AYI schemes are not autonomous, self-financing, and grassroots. AYI staff and network administrators actively oversee and manage their schemes, which is necessary for the organization to reach its stellar 80% re-contribution rate for members (Oyaya et al, 2015: 12). In fact, the CBHIs form an interdependent network of schemes that coordinate and share financing. AYI operates two networks: one for Nyeri county and one for Kirinyaga county. Together, these two networks have 35,000 direct beneficiaries and members attain health insurance benefits through the network.

[1] Funded by Evangelischer Entwicklungs- Dienst (faith-based NGO) and Bread of the World-Berlin

It works in the following way: through AYI, the CBHI offers subsidized health insurance options to members. The most affordable public hospital package costs 770 KES annually ($7.46 USD) (59). Depending on the beneficiaries, AYI also offers inpatient coverage through NHIF. This partnership with NHIF is important, because the NHIF package is offered alongside AYI's other microinsurance packages. Wealthier scheme members who want expanded coverage can opt into the NHIF package, which is 6,000 KES annually ($58.28 USD). This acts as a network cross-subsidy for cheaper packages (Kimball et al, 2013: 24). Members can then submit claims to the network to use their health benefits.

An important design feature is the re-insurance fund. In case there are annual losses due to claims, each network has a fund in place to cover health costs for members. This is a key point: the networks are not financially autonomous and depend on overhead funding. AYI replenishes the re-insurance fund each year, and it can be used for comprehensive health needs. In practice, AYI's CBHI schemes have overhead costs, financial interdependence, cross-subsidized insurance packages, and active scheme/network management.

Expanded Health Coverage for Beneficiaries

CBHI insurance schemes provided by AYI offer a number of healthcare coverage options for beneficiaries. AYI offers three health insurance packages that households can purchase, which are discussed below (Koven et al, 2014: 4).

Small Household Package – This is AYI's most popular product, and it is used by 71% of households in the AYI network. This package is designed for low income households. The annual insurance premium is $8 USD (700 KSH). It covers cashless inpatient and outpatient coverage at network locations for the contributor, spouse, and children under 18. These network locations include clinics, hospitals, and specialized health centers. Under this package, all household beneficiaries are entitled to inpatient and outpatient coverage at their closest network location. Finally, the package covers $229 USD per hospital visit.

Enlarged Household Package – This is an expansion of AYI's small household package. It allows households to add family members to their plan. Specifically, households can add grandchildren as well as children between 18 and 25 who are current students. The annual premium increases on the margins: the price is $8 USD plus $1.14 per additional person.

NHIF Plus – As we will discuss in the next section, AYI offers NHIF insurance packages through a formal partnership deal. This insurance package is the most comprehensive, but it is also the most expensive by a large margin. This package adds increased cashless hospital coverage for beneficiaries to access healthcare at private sector hospitals and missions. The package also covers an additional $115 USD above NHIF coverage. However, the cost of the NHIF Plus package is $26.35 USD and is only used by a minority of higher income beneficiaries in the AYI CBHF network.

Broadly, health insurance can lower the cost of healthcare utilization in Kenya. Family planning needs such as birth control pills, IUDs, and condoms, HIV testing and counseling, and more cost money for uninsured households. While many of these needs are subsidized by NGOs and faith-based organizations, there still exists a severe lack of access for Kenyans (especially in rural areas). Insurance coverage covers the costs of these needs, in addition to the costs of hospital visits, that would otherwise go to uninsured households. Expanded healthcare insurance coverage can thus shift behaviors for households and incentivize them to utilize family planning, HIV counseling, and other forms of healthcare.

Stakeholders

AYI's CBHI schemes are facilitate by six primary stakeholders other than AYI (Oyaya et al, 2015).

1. District hospitals: coordinate with CBHIs process claims and provide health services
2. NHIF county-level officials: formal partnership with AYI to offer NHIF health insurance package. CBHI schemes are classified as "NHIF agencies", and AYI negotiated a 5% agency fee for each of its members that sign up for the NHIF package. From the perspective of NHIF, AYI is a strategic partnership for the organization to make inroads into enrolling Kenyans working in the informal sector or living in rural areas (Kimball et al, 2013: 57).
3. Ministry of Health (MOH) county-level officials: encourage and facilitate efforts to establish CBHIs. In 2015, Nyeri county MOH gave AYI a letter of commitment to assist in scaling up its programs, but nothing has come of it with regards to resource mobilization.
4. Chiefs at CBHI sub-locations: key partner at CBHI locations. They promote CBHIs to local residents and work with AYI staffers.
5. KCBHFA officials: work on national level to lobby for universal healthcare and visibility of CBHIs. They also provide technical support to AYI staff, including knowledge sharing, marketing training, monitoring & evaluation implementation, and the salary cost for a CBHI promoter for two years.
6. Donor agencies

AYI's organizational model is as follows. The organization is made up of six primary staffers. In addition, networks have their own staff (Nyeri has two staffers and Kirinyaga has three staffers). Theoretically, the network would fund its own staff salaries, but that goal had not been realized as of 2015 (Oyaya et al., 2015: 56). AYI originally planned to share the salary costs and phase out their support over the course of Phase 2, but they did not reach that mark. Again, this points out a recurring and distinguishing feature of AYI CBHI schemes: overhead costs such as the re-insurance fund and salaries for network administrators are key features.

AYI staffers

Section/Department	No.	Responsibilities
C.E.O/Programme Coordinator	1	C.E.O/project coordinator and head of Research and Marketing department
Risk Management & M&E	1	Also serves as Programme officer, responsible for Nyeri, M&E, field officer and supervisor of Network Agents
Training & Development	1	Also serves as Programme officer, responsible for Kirinyaga, field officer and supervisor of Network Agents
Administration & Finance	1 Finance officer, 1 Admin. Assistant & 2 Drivers	• Financial management, project accounting • Support services

Network staffers

Network	Network Assistants	Admin. Assistant	Remarks
Nyeri	2 males	None	Staff costs for 1 NA are covered by AYI
Kirinyaga	1 male 1 lady	1 lady	Staff costs of one NA are fully catered for by the NW while the other NA and Admin. Assistant costs are covered by AYI
Muranga	None	None	Expected to be operational in January 2016

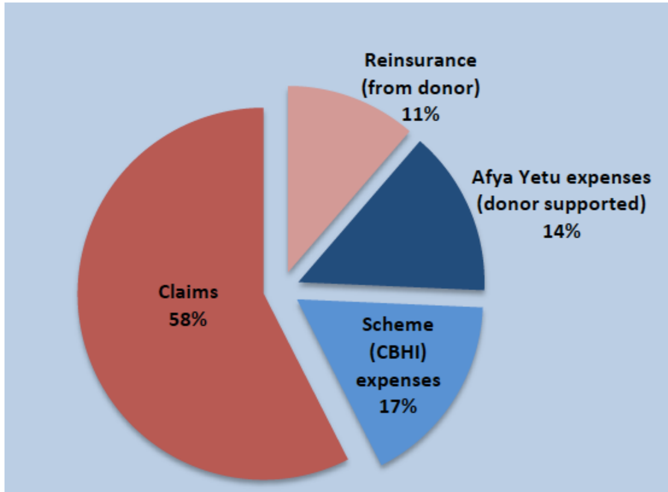
Sustainability

AYI's CBHI schemes have been resilient; all 86 schemes that were launched between 2009 and 2015 are still fully operational (interview with AYI). As we have discussed, AYI's design features, partnerships, and organizational model are a blueprint for their success. In short, AYI has shown that it can work over the medium-term on the local and county levels. However, a 2015 independent evaluation pointed out two potential sustainability issues that both come down to funding. First, AYI staff dedicates a significant amount of its limited time writing grant proposals to various agencies for funding (Oyaya et al., 2015: 42). Second, recurring overhead costs cannot be minimized as the program scales up. This includes staff salaries, the re-insurance fund, and salaries for network managers.

Despite funding issues, CBHI schemes cater to a wide network of members. Assuming CBHI schemes increase healthcare utilization and reduce out-of-pocket costs, the relative cost per member for AYI is low. While a cost-effectiveness analysis is outside the scope of this paper, it is important to point out that the overhead costs are administrative and don't finance the cost of the intervention itself (other than the re-insurance fund). As long as claim expenditures are largely met by CBHI contributions, the overhead costs are relatively efficient.

Costs

According to one report, AYI has the following expenditure breakdown. Donors fund 25% of total project costs: 14% from overhead expenses and 11% from the re-insurance fund (Koven et al, 2014).



Measuring success

At the end of Phase 2 (2015), AYI commissioned an independent evaluation of their work in the past six years (Oyaya et al., 2015). This evaluation carried out a survey from random samples (using cluster sampling techniques) of CBHI members. Here, I will report some of the areas where AYI did not meet its benchmarks. This helps us understand how to measure the success of the program purely from an implementation perspective.

With regards to penetration, about 85.2% of members were registered in a CBHI for more than two years (vii). The penetration rate (defined as percent of participation in the community) of both networks is 11.91%, which did not meet its goal of 30% by the end of Phase 2. AYI also failed to meet its 2015 benchmarks of 65,000 beneficiaries, falling significantly short of that goal at 35,000. The evaluation pointed out institutional and management factors that led to this (26-27). Commodity price fluctuations had an impact on local economies and reduced the marginal propensity of new members to buy premiums. Additionally, local resource persons who were identified to train and launch CBHI schemes wanted salaries, which were outside AYI's budget. While AYI did not meet its penetration and beneficiary goals, it still grew in a sustainable way.

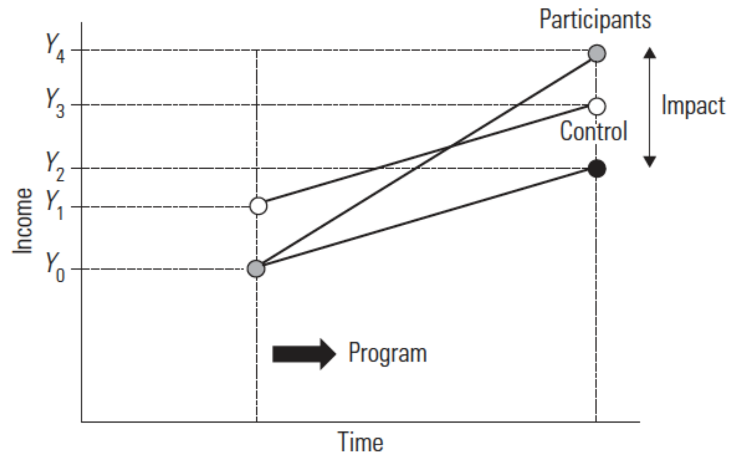
Moving forward, the evaluation recommends strengthening certain aspects of AYI's organizational model. This includes institutional development at the secretariat level and scaling up service delivery in new areas to gain members. Additionally, the evaluation recommends market sensitization campaigns through partnerships with local FM stations, road shows, toll free calls, social media outreach, and mobile health (28). Both these suggestions are geared towards market penetration and program scale. As such, these two features form a framework with which we can measure AYI's implementation success.

V. Theoretical Analysis: Impact of CBHF Schemes

Afya Yetu Initiative has steadily grown since 2009. AYI has had significant success with CBHF sustainability – all 86 of the schemes it launched between 2009 and 2015 are fully operational (as of April 2017). However, there is little conclusive evidence that community-based health insurance financing improves health utilization for participants in a meaningful way. According to a World Bank literature review on CBHF schemes, "CBHIs are a new and emerging social protection technology in many parts of the developing world. Track records are short, and empirical evidence upon which conclusions about impact and sustainability can be reached are limited" (Tabor, 2005). There is even less evidence for whether CBHF schemes increase health utilization in the East African context.

While sparse, the empirical literature that does exist on CBHF schemes is focused on program uptake. A 2002 journal article uses principle components analysis to examine various factors in Kenya "that hinder or facilitate use of medical insurance so that these factors can be considered when institutionalizing insurance in communities" (Mwabu et al., 2002). A 2011 article uses contingent valuation methods to ask uninsured people in Tanzania their willingness-to-pay for community health insurance schemes. This article points out that only 30% of rural households were willing to pay higher insurance premiums to cross-subsidize the poor, and that "communities need to be sensitized about the existence of the CHF/TIKA to encourage enrollment" (Joachim et al., 2011). Perhaps the harshest critique on the existing empirical evidence comes from a 2015 article that examines three randomized control trials in India. The article cites methodological flaws in the RCTs, and specifically highlights the inability of the experiments to control for selection on unobservables. The study concludes that "CBHI schemes of the type examined in this paper are unlikely to have a substantial impact on access and financial protection in developing countries" (Raza et al., 2015). In sum, there is little conclusive evidence about the impact of CBHF schemes on health behavior once uptake has occurred.

In this paper, I use quasi-experimental techniques to establish a causal link between AYI's CBHF schemes and healthcare utilization in Kenya. Using difference-in-difference (DID) analysis, I examine health behaviors and relative household wealth of people living near a CBHF scheme. DID is an ex post evaluation methodology that where outcomes are compared for two groups in two time periods. One group, which is exposed to the intervention, is assigned to the treatment group. The other group has no exposure to the intervention. The difference between the groups in the first period is subtracted from the difference between the two groups in the second period. This generates a "double difference" that isolates the impact of the intervention. See below for a visualization of DID. Under this model, DID = $(Y_4 - Y_0) - (Y_3 - Y_1)$, where Y_i is the outcome variable.



Source: Khandker et al., 2010

One major strength of DID is that the subtraction between groups in both periods removes fixed but unobservable differences between units in both groups. In other ex post causal analyses, the researcher can only adjust for observable differences. DID assumes that unobserved heterogeneity exists between units in the control and treatment groups, and thus removes those biases through subtraction over two time periods. However, DID has some limitations. It assumes that heterogeneity between groups is time invariant. In other words, the difference between groups remains constant over time. This is called the parallel trends assumption, and it can be implausible for several reasons. Moving forward, we assume time invariant heterogeneity between our control and treatment groups.

The formal equation for DID is specified in the following way:

$$Y_{it} = \alpha + \beta D + \varphi T + \delta DT + \varepsilon_{it}$$

In this model, D is a dichotomous variable for whether the unit is in the treatment or control group. T is a dichotomous variable for the time period. The coefficient δ on the interaction term DT represents the isolated DID impact of outcome Y on the treatment group.

VI. Empirical Analysis

Using the model outlined above, I examine the impacts of CBHF schemes on healthcare utilization and household wealth in Kenya. I apply the generic estimation equation for DID, with the addition of various covariates, to three separate models. The first is a linear probability model on health behaviors. I examine the impact of CBHF schemes on four dichotomous outcome variables: use of condom method, AIDS testing, health insurance coverage, and use of contraceptives. I look at male and female respondents combined, I stratify by gender, and I also estimate a model just for those from poor households. Poor households are defined as households that are in the bottom two quintiles on the DHS wealth index ranking, which I will elaborate on further in the paper. This simply tests the theory that AYI CBHF schemes achieved various health behaviors.

The second model looks at household wealth. I test three outcome variables that are proxies for relative wealth, to test the theory that CBHF schemes create household wealth by lowering overall health expenditures. I test the following outcomes: relative wealth, number of assets, and number of mosquito nets owned. I test these outcome variables for all households in the sample, and also on the following stratified samples: households headed by males, households headed by females, and poor households.

The third model focuses specifically on maternal health. Specifically, I examine a population of survey respondents who are mothers. I test four outcome variables among mothers to test the theory that CBHF schemes increase healthcare utilization for mothers. These outcomes are the following: contraceptive use, recent visit to a health facility, weight, and health insurance coverage. I look at outcomes for all mothers, in addition to comparing poor and non-poor mothers.

To understand what I am measuring, it's important to understand how I assign the treatment and control groups. AYI runs CBHF sublocations in two Kenyan counties: Nyeri and Kirinyaga. I assign units to the treatment group if they live within 5 kilometers of a CBHF scheme. Units assigned to the treatment groups are 'potentials' for receiving treatment (i.e. participating in the CBHF scheme). To be clear, the treatment is defined as the option to join a CBHF scheme or have geographic feasibility of joining. I assign units to the control group from a separate, but demographically similar, county. I then run my model comparing the units assigned to the control group and the units assigned to the treatment group (even if they did not actually receive the treatment). This gives me the average treatment effect (ATE), which measures the average effect of the CBHF scheme on an individual living within 5 kilometers of the program. I have two justifications for measuring ATE rather than treatment on the treated (TOT). One, I do not have any information on direct CBHF participants. Two, ATE reveals the effect of CBHF schemes on the whole community, rather than on a subset who signed up and may be selected in certain ways.

Data Sources

To construct my datasets and assign units to the treatment and control groups, I use three data sources:

1. 2009 Kenya Demographic and Health Survey (available publicly)
2. 2014 Kenya Demographic and Health Survey (available publicly)
3. AYI sublocation data (obtained through correspondence with Afya Yetu Initiative)

The Demographic and Health Survey (DHS) surveys contain health data on survey respondents throughout Kenya. The surveys are collected using stratified and cluster sampling techniques. DHS is a program funded by USAID, various donors, and participating countries. Standard DHS surveys are conducted in countries approximately every five years, and surveys are nationally representative. DHS conducts surveys in survey clusters, in which they interview various sub-populations. Each sub-population has its own survey questionnaire, designed for that group. I create datasets from DHS survey datasets, which are provided separately for each different sub-population. Below is a summary of each sub-population.

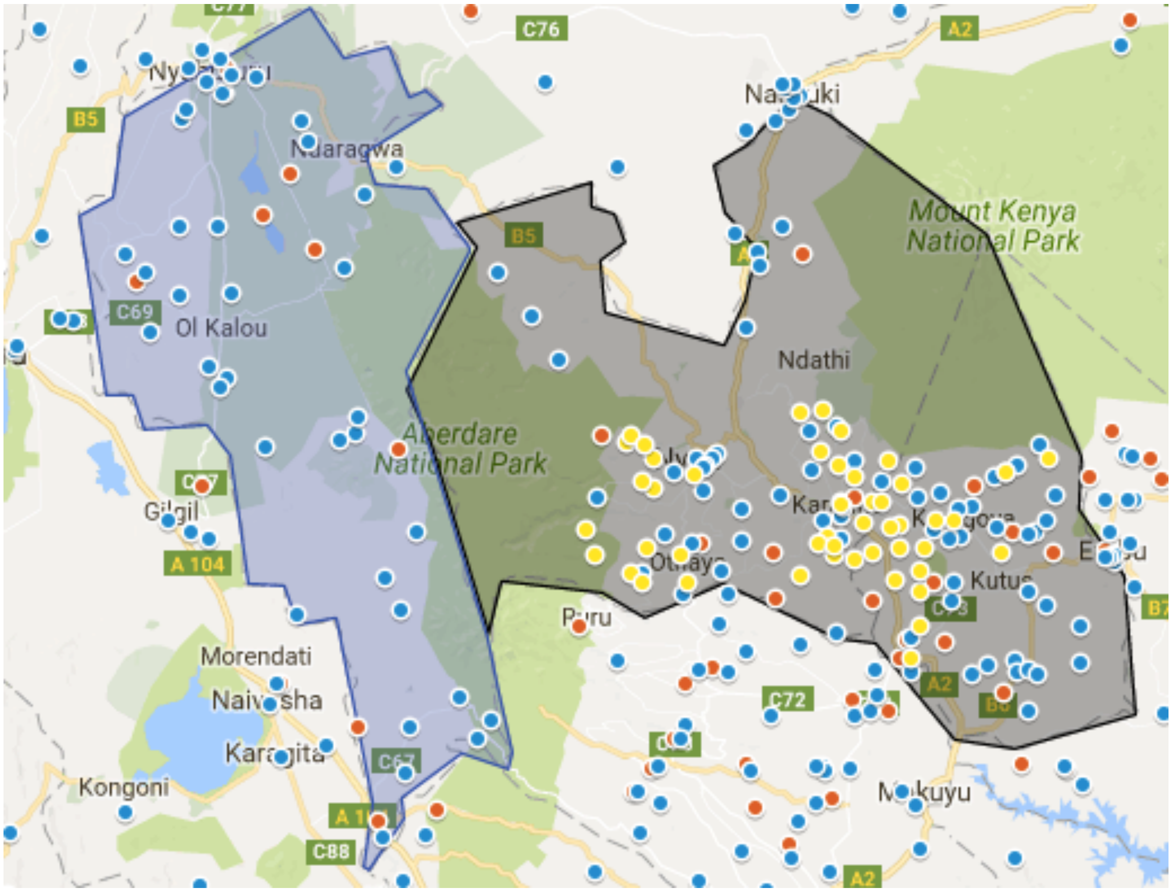
1. Household-level: This data only includes heads of households as survey respondents. The data includes household-level data and a household roster, in addition to specific information about the head of household. Variables include household information such as wealth level, assets, and physical household structure. While the respondent is the head of household, the unit of analysis in this dataset is the household.
2. Individual women: This dataset has one observation for every eligible woman in the survey cluster sample. Survey respondents include individual women from households. Variables include health indicators such as contraceptive use and health visits. A female in this dataset is eligible if she is of reproductive age (between 15 and 49).
3. Individual males: This dataset has one observation for every eligible male in the survey cluster samples. Survey respondents only include individual men form households. Variables include health indicators such as condom use. A male in this dataset is eligible if he is between the ages of 15 and 59.
4. Birth's Recode (BR): This dataset includes the full birth history for all mothers interviewed in the survey cluster samples. Survey respondents only include mothers of children born in the last 5 years. Variables include broad health indicators and maternal-specific indicators such as pregnancy and postnatal care.

To assign units to my treatment group, I plot the 2009 and 2014 DHS survey clusters on a map, in addition to mapping the sublocations for each AYI scheme launched between 2009 and 2014. All of these AYI sublocations exist within the two counties of Nyeri and Kirinyaga. At each sublocation, AYI recruits local leaders and volunteers to spread awareness about the CBHI scheme. Local residents can register for CBHI insurance packages at the sublocations, and each sublocation acts as a unit in the CBHI network. Participants can submit insurance claims through their sublocation, which sends the claim to the network. Survey clusters from 2009 and 2014 that are within 5 kilometers of an AYI sublocation are assigned to the treatment group. I use 5 kilometers as a way to describe "proximity to CBHI scheme." I choose 5 kilometers to capture the radius of the sublocation without creating an area that is larger than the boundaries of the village or town.

To assign units to the control group, I avoid choosing any DHS survey clusters within Nyeri or Kirinyaga counties. Even though DID accounts for unobserved and observed heterogeneity between treatment and control groups, it is still important to identify roughly similar units. Using DHS survey data, I examined the 47 counties across two key dimensions: average number of household members and average household wealth (the units for household wealth are on a "wealth score" scale designed by DHS). This let me find a demographically similar county in which I could choose my control group. As we can see in the scatter plot below, Nyandarua county is similar to Nyeri and Kirinyaga across these dimensions. On a closer examination, Nyandarua county also borders Nyeri, has a similar agricultural export based economy, and has a similar proportion of rural and urban people. Most importantly, a review of CBHI schemes in Kenya tells us that there is no major CBHI scheme in Nyandarua. This reduces the potential issue of contamination. As such, I choose all the 2009 and 2014 DHS survey clusters from Nyandarua county and assign them to my control group.

Source: Demographic and Health Surveys

Below, I present a map of the region that I focus on within Kenya. The red dots are DHS survey clusters from 2009. The blue dots represent DHS survey clusters from 2014. The yellow dots represent AYI CBHF sublocations. The black shaded area is Nyeri county and Kirinyaga county. Finally, the blue shaded area is Nyandarua county. To restate, I choose clusters from Nyandarua county and assign them to my control group. I choose clusters that are within 5 kilometers of CBHF sublocations and assign them to my treatment group.



Testing Covariates

While DID adjusts for time invariant heterogeneity between the control and treatment groups, the parallel trends assumption is somewhat implausible. It is generally unlikely that two different groups will have an equal socioeconomic rate of change. To interrogate and strengthen the parallel trends assumption, I identify potential covariates for each model that could be ‘time varying’. By adding these covariates to the DID regression model, I can adjust for these observable factors and strengthen the parallel trends assumption. But before I can add these to the equation, it’s important to confirm that they are contributing to the model in some way. There are multiple formal tests that can be conducted to measure whether a covariate is adding anything to the model, and I apply two tests to see whether my list of potential covariates should be added. I do these covariate tests for different potential covariates in all three models.

The first test I apply is adjusted-R^2. I run regressions for different blocks of covariates and examine which block adds the most. Adjusted-R^2 only increases when covariates improve the accuracy of the model by explaining some of the variation. The block of covariates with the highest adjusted –R^2 adds the most to the regression model. The second test I apply is the Akaike Information Criterion (AIC) criterion. This is a formal tool for model selection, and reports a number for the model with the highest quality. The lowest number in the AIC criterion has the highest level of accuracy. Again, I test covariate blocks in different regression models to calculate the AIC and thus determine how much accuracy they are adding. In Appendix I, you can find the outputs of these covariate tests.

Below are results from covariate tests. Covariates that pass both tests are included. For each model, I choose different covariates to test based on a combination of economic theory and a goal to identify time varying variables that could cause bias in my model.

Linear Probability Model on Health Behaviors	Type	Passes adjusted-R^2 & AIC test?
Age of respondent	Continuous	TRUE
Years of education	Continuous	TRUE
Number of HH members	Continuous	FALSE
Age of HH head	Continuous	FALSE
Literacy level	Continuous	TRUE
Wealth index factor score (i.e. relative wealth score)	Continuous	TRUE
Total children born	Continuous	FALSE
Currently working	Dichotomous	TRUE
Currently married	Dichotomous	TRUE

Household Wealth Model	Type	Passes adjusted-R^2 & AIC test?
Age of HH head	Continuous	TRUE
Years of education	Continuous	TRUE
Number of HH members	Continuous	TRUE
Sex of HH head	Dichotomous	TRUE
Number of children under 5	Continuous	TRUE
Owns bednet for sleeping	Dichotomous	TRUE

Maternal Health Outcomes Model	Type	Passes adjusted-R^2 & AIC test?
Age of respondent	Continuous	TRUE
Age of respondent during 1st birth	Continuous	TRUE
Years of education	Continuous	TRUE
Number of HH members	Continuous	TRUE
Wealth index factor score (i.e. relative wealth score)	Continuous	TRUE
Total children born	Continuous	TRUE
Currently working	Dichotomo	TRUE
Sex of HH head	Dichotomo	TRUE

Additionally, I assess the presense of heteroscedasticity in the error terms. I don't test for heteroscedasticity in the linear probability model, but only for the other two models. The linear probability model has a dichotomous outcome, which already tells us that heteroscedasticity exists. For the other two models, I use both informal visualization and formal tests to look for heteroscedasticity. I find that my model likely contains some heteroscedasticity, and thus adjust my regressions for robust standard errors. You can find the results of my heteroscedasticity tests in Appendix II.

Summary Statistics

Below, I present tables of summary statistics on key variables I use in my three difference-in-difference models. These tables present the means of these variables for the control and treatment groups, as well as the difference between their means. I compare these means across stratified groups from the sample. Importantly, these means are only from 2009, or the pre-intervention period. These tables are meant to provide us with a baseline understanding of these variables before we analyze them in the results section.

Linear Proability Model		Total	Male	Female	Poor
Condom method used (1 = Yes, 0 - No)	Control	0.30	0.39	0.18	0.30
	Treatment	0.30	0.37	0.19	0.40
	Difference	0.00	0.02	0.01	0.10
Covered by health insurance (1 = Yes, 0 - No)	Control	0.11	0.16	0.09	0.02
	Treatment	0.10	0.11	0.09	0.02
	Difference	0.01	0.05	0.00	0.00
Ever been tested for AIDS (1 = Yes, 0 - No)	Control	0.52	0.38	0.58	0.49
	Treatment	0.62	0.39	0.72	0.42
	Difference	0.10	0.01	0.14	0.07
On birth control (1 = Yes, 0 - No)	Control	0.36	0.44	0.32	0.30
	Treatment	0.34	0.38	0.32	0.26
	Difference	0.02	0.06	0.00	0.04

Household Wealth Model		Total	Male	Female	Poor
Wealth index ranking (Range: -142008 to 309844)	Control	9447.48	2468.55	24149.81	-89962.84
	Treatment	51787.42	53564.79	46543.68	-96749.42
	Difference	42339.94	51096.24	22374.67	6786.58
Number of assets (0 - 10)	Control	3.16	3.27	2.91	1.43
	Treatment	3.33	3.36	3.26	1.03
	Difference	0.18	0.09	0.35	0.40
Number of mosquito nets owned	Control	1.15	1.16	1.12	1.18
	Treatment	1.36	1.34	1.40	1.00
	Difference	0.21	0.18	0.28	0.18

Maternal Health Behavior Model		Total Mothers	Poor Mothers	Non-poor Mothers
Currently using contraceptive (1 = Yes, 0 - No)	Control	0.44	0.38	0.57
	Treatment	0.44	0.30	0.53
	Difference	0.00	0.08	0.04
Visited health facility in last 12 mos. (1 = Yes, 0 - No)	Control	0.55	0.56	0.52
	Treatment	0.51	0.47	0.53
	Difference	0.04	0.09	0.01
Weight (kilos)	Control	67.22	58.54	84.53
	Treatment	63.13	55.83	75.01
	Difference	4.08	2.71	9.52
Covered by health insurance (1 = Yes, 0 - No)	Control	0.08	0.04	0.16
	Treatment	0.11	0.00	0.19
	Difference	0.03	0.04	0.03

Many of the results above make intuitive sense. For instance, the poor (defined as being in the two lowest wealth index quintiles) are on average less covered be health insurance, lower on the wealth index, and own fewer assets. We can also observe that, with a few exceptions, the treatment and control groups in the baseline are quite similar across many variables. It will be interesting to see how this changes in the DID analysis.

VII. Results

Linear Probability Model on Health Behavior

A linear probability model involves a dichotomous outcome variable. In the context of DID analysis, a linear probability model estimates probability of the outcome for people assigned to the treatment group. For instance, if the outcome variable is a dichotomous variable for "enrolled in health insurance", the coefficient β would be interpreted as "an individual living near an AYI CBHF scheme has a β*100% change in probability of being enrolled in health insurance than an individual not living near a scheme." I choose four health behavior outcomes to test using this model.

1. Uses condom
2. Has ever been tested for AIDS
3. Has health insurance
4. Uses birth control

Below, I report the results of my DID analysis for four sub-populations in the treatment and control groups: total, poor, male, and female. Poor is defined as being below the 40th percentile (or bottom two quintiles) of the DHS wealth index factor score.

Total

LPM, Total Number of Observations	Condom method used 923	Been tested for AIDS 1574	Has health insurance 1577	On birth control 1578
treatment	-0.007 (0.06)	0.080 (0.05)	-0.066** (0.02)	-0.016 (0.03)
year	-0.214*** (0.04)	0.193*** (0.04)	0.020 (0.02)	-0.082* (0.03)
treatment*year	0.040 (0.06)	-0.079 (0.06)	0.191*** (0.04)	0.250*** (0.05)
Age of respondent	-0.006*** (0.00)	0.004** (0.00)	0.005*** (0.00)	0.010*** (0.00)
Years of education	-0.005 (0.00)	0.001 (0.01)	-0.018*** (0.00)	0.017*** (0.00)
Number of HH members	-0.015** (0.01)	-0.002 (0.01)	0.003 (0.00)	-0.008 (0.00)
Literacy level	0.016 (0.02)	0.008 (0.03)	0.011 (0.01)	0.082*** (0.02)
Wealth index factor score (i.e. relative wealth score)	-0.000* (0.00)	0.000*** (0.00)	0.000*** (0.00)	0.000* (0.00)
Currently working	0.080 (0.04)	0.045* (0.02)	0.030* (0.01)	0.079** (0.03)
Constant	0.492*** (0.07)	0.355*** (0.10)	-0.014 (0.05)	-0.177** (0.06)

b / se. * = p < .05; ** = p < .01; *** = p < .001

Poor

LPM, Poor Number of Observations	Condom method used 379	Been tested for AIDS 701	Has health insurance 574	On birth control 702
treatment	0.151 (0.13)	-0.044 (0.06)	0.002 (0.02)	0.001 (0.05)
year	-0.228** (0.07)	0.257*** (0.07)	0.033 (0.03)	-0.036 (0.05)
treatment*year	-0.101 (0.13)	0.060 (0.08)	0.037 (0.05)	0.173* (0.08)
Age of respondent	-0.002 (0.00)	-0.000 (0.00)	0.002 (0.00)	0.009*** (0.00)
Years of education	0.009 (0.01)	0.007 (0.01)	-0.006 (0.00)	0.025*** (0.01)
Age of HH head	0.001 (0.00)	-0.003* (0.00)	0.000 (0.00)	-0.003* (0.00)
Literacy level	0.023 (0.02)	0.015 (0.04)	0.000 (0.02)	0.086** (0.03)
Wealth index factor score (i.e. relative wealth score)	-0.000 (0.00)	0.000 (0.00)	0.000* (0.00)	0.000** (0.00)
Married	-0.084* (0.04)	0.129** (0.05)	-0.009 (0.02)	0.148*** (0.04)
Constant	0.203 (0.13)	0.529** (0.18)	0.047 (0.06)	-0.039 (0.11)

b / se. * = p < .05; ** = p < .01; *** = p < .001

Male

LPM, Males Number of Observations	Condom method used 435	Been tested for AIDS 566	Has health insurance 567	On birth control 567
treatment	0.056	-0.038	-0.124**	-0.068
	(0.08)	(0.06)	(0.04)	(0.06)
year	-0.213***	0.201***	-0.059	-0.246***
	(0.06)	(0.06)	(0.04)	(0.05)
treatment*year	-0.016	0.053	**0.310*****	**0.403*****
	(0.08)	(0.08)	(0.06)	(0.08)
Age of respondent	-0.000	-0.000	0.004	0.003
	(0.00)	(0.00)	(0.00)	(0.00)
Years of education	-0.002	-0.014	-0.022***	0.004
	(0.01)	(0.01)	(0.01)	(0.01)
Literacy level	0.026	0.019	0.022	0.121**
	(0.04)	(0.04)	(0.02)	(0.04)
Wealth index factor score (i.e. relative wealth score)	-0.000	0.000***	0.000***	0.000*
	(0.00)	(0.00)	(0.00)	(0.00)
Currently working	0.252***	0.220***	0.059	0.238***
	(0.07)	(0.07)	(0.04)	(0.06)
Currently married	-0.365***	0.090	0.040	0.058
	(0.06)	(0.06)	(0.04)	(0.06)
Constant	0.296**	0.183	0.045	-0.116
	(0.11)	(0.11)	(0.07)	(0.10)

b / se. * = p < .05; ** = p < .01; *** = p < .001

Female

LPM, Females Number of Observations	Condom method used 460	Been tested for AIDS 978	Has health insurance 981	On birth control 982
treatment	0.017	0.125*	-0.040	-0.005
	(0.08)	(0.06)	(0.02)	(0.04)
year	-0.165***	0.278***	0.081*	0.057
	(0.05)	(0.04)	(0.03)	(0.04)
treatment*year	0.004	-0.164*	0.095	0.145*
	(0.08)	(0.07)	(0.05)	(0.06)
Age of respondent	0.001	-0.002	0.007***	0.006**
	(0.00)	(0.00)	(0.00)	(0.00)
Years of education	-0.001	-0.000	-0.016***	0.021***
	(0.01)	(0.01)	(0.00)	(0.01)
Wealth index factor score (i.e. relative wealth score)	-0.000	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Total children born	-0.011	0.038*	-0.010	0.045***
	(0.01)	(0.02)	(0.01)	(0.01)
Currently working	0.007	0.053*	0.020	0.053*
	(0.02)	(0.02)	(0.01)	(0.02)
Constant	0.178**	0.507***	-0.022	-0.105
	(0.06)	(0.08)	(0.05)	(0.06)

b / se. * = p < .05; ** = p < .01; *** = p < .001

According to these results, condom usage and AIDS testing has not significantly increased for the treatment group. The results also, somewhat alarmingly, tell us that there is potentially a reduction in the probability of being tested for AIDS for women in the treatment group. However, CBHFs theoretically pose no imposition on AIDS testing, so this result can likely be attributed to confounding factors and sample size. The model does show a positive increase in health insurance enrollment and use of birth control. In total, a person living near a CBHF scheme has a 19.1% higher probability of being enrolled in health insurance. For males, this probability is even higher at 31%, while women only have a 9.5% higher probability of being enrolled in health insurance. However, poor people living nearby a CBHF scheme do not have a significantly higher probability of being enrolled in health insurance. This seems to indicate that CBHF scheme enrollment disproportionately favors those with at least some relative wealth. Finally, individuals in the treatment group have a 25% higher probability of using some kind of birth control. In particular, men benefit the most from this with a 40.3% higher probability of using birth control.

In sum, the linear probability model tells us that people living near a CBHF scheme have a higher probability of being enrolled in a scheme and using birth control. Men are the largest beneficiaries, but women also see gains in enrollment and use of birth control. This model also indicates that the poor benefit less from CBHF schemes, at least in terms of enrollment.

Household Wealth Model

I also ran a DID analysis on variables for household wealth. This is based on the household-level dataset, and the For this model, I use a log-level functional form in which I transform each dependent variable onto a natural logarithmic scale. I have three reasons for doing this. One, a logarithmic scale achieves normalization among the dependent variables, which makes them comparable metrics that can act as proxies for household wealth. Two, because of our strong suspicion of heteroscedasticity (see Appendix II), a logarithmic likely improves the model by creating a more normal distribution. Third, a log-level functional form allows us for better interpretation of the DID coefficient. Using log-level, we can interpret the DID coefficient δ as "100* δ % increase in the dependent variable as a result of assignment to the treatment group." Below are the three (transformed) outcomes variables I test using the household wealth model.

1. ln(wealth index factor score) – the wealth index factor score for each household is compiled by DHS using principle component analysis
2. number of assets – a continuous variable from 0 to 10, with each additional number signifying ownership of an asset (i.e. car, refrigerator, bicycle, watch, radio, etc.).
3. ln(number of mosquito nets owned)

Below, I report the results of my DID analysis for four sub-populations: total, poor, male, and female. Again, poor is defined as being below the 40th percentile (or bottom two quintiles) of the DHS wealth index factor score.[2]

Head of Household – Total

Household Savings, Total Number of Observations	Wealth index factor score 899	Number of assets 1397	Number of mosquito nets owned 696
treatment	0.058 (0.08)	0.038 (0.14)	0.011 (0.04)
year	-0.422*** (0.11)	0.361** (0.13)	-0.081 (0.07)
treatment*year	0.148 (0.13)	0.155 (0.18)	0.189* (0.08)
Years of education	0.201*** (0.04)	0.722*** (0.06)	0.058** (0.02)
Age of HH head	-0.008** (0.00)	-0.003 (0.00)	0.000 (0.00)
Number of HH members	-0.036 (0.02)	0.060** (0.02)	0.098*** (0.01)
Sex of HH head	0.112 (0.07)	-0.383*** (0.10)	0.085* (0.04)
Number of children under 5	0.066 (0.06)	-0.313*** (0.07)	-0.089** (0.03)
Owns bednet for sleeping	0.367*** (0.07)	0.684*** (0.10)	0.000 (.)
Constant	11.014*** (0.17)	2.304*** (0.25)	-0.036 (0.10)

[2] For the 'poor' sub-population, I use a level-level functional form for wealth index factor score.

b / se. * = p < .05; ** = p < .01; *** = p < .001

Head of Household – Poor

Household Savings, Poor Number of Observations	Wealth index factor score 333	Number of assets 260	Number of mosquito nets owned 150
treatment	-6374.805*	-0.256	-0.056
	(2853.15)	(0.15)	(0.09)
year	48737.887***	0.919***	-0.179
	(2353.77)	(0.16)	(0.16)
treatment*year	7142.127	-0.264	0.198
	(3926.49)	(0.25)	(0.21)
Years of education	4522.498**	0.258**	0.060
	(1520.85)	(0.10)	(0.06)
Age of HH head	23.942	0.001	-0.005
	(63.25)	(0.00)	(0.00)
Number of HH members	82.876	0.025	0.085***
	(483.56)	(0.03)	(0.02)
Sex of HH head	-1502.489	-0.478***	0.111
	(1963.24)	(0.13)	(0.08)
Number of children under 5	-3824.709**	-0.116	-0.072
	(1224.75)	(0.08)	(0.05)
Owns bednet for sleeping	3279.326	0.656***	0.000
	(2107.58)	(0.14)	(.)
Constant	-92025.062***	1.254***	0.143
	(5034.73)	(0.33)	(0.19)

b / se. * = p < .05; ** = p < .01; *** = p < .001

Head of Household – Male

Household Savings, Male Number of Observations	Wealth index factor score 663	Number of assets 1003	Number of mosquito nets owned 502
treatment	-0.010 (0.10)	-0.027 (0.16)	-0.056 (0.09)
year	-0.483*** (0.14)	0.606*** (0.16)	-0.179 (0.16)
treatment*year	0.234 (0.16)	0.135 (0.21)	0.228* (0.10)
Years of education	0.161** (0.05)	0.769*** (0.07)	0.060* (0.03)
Age of HH head	-0.006* (0.00)	0.004 (0.00)	0.004* (0.00)
Number of HH members	-0.058* (0.03)	0.028 (0.03)	0.080*** (0.01)
Number of children under 5	0.122 (0.07)	-0.261*** (0.08)	-0.061 (0.03)
Owns bednet for sleeping	0.494*** (0.08)	0.781*** (0.12)	0.000 (.)
Constant	11.184*** (0.17)	1.515*** (0.25)	-0.050 (0.10)

b / se. * = p < .05; ** = p < .01; *** = p < .001

Head of Household – Female

Household Savings, Female Number of Observations	Wealth index factor score 236	Number of assets 394	Number of mosquito nets owned 194
treatment	0.255 (0.15)	0.052 (0.09)	-0.006 (0.08)
year	-0.371* (0.16)	-0.117 (0.08)	-0.115 (0.12)
treatment*year	-0.089 (0.22)	0.035 (0.12)	0.115 (0.16)
Years of education	0.297*** (0.06)	0.175*** (0.03)	0.046 (0.04)
Age of HH head	-0.008* (0.00)	-0.003 (0.00)	-0.004* (0.00)
Number of HH members	0.021 (0.05)	0.038** (0.01)	0.128*** (0.02)
Number of children under 5	-0.088 (0.09)	-0.119* (0.05)	-0.114* (0.05)
Owns bednet for sleeping	0.002 (0.12)	0.145* (0.07)	0.000 (.)
Constant	11.119*** (0.26)	0.813*** (0.14)	0.298* (0.15)

b / se. * = p < .05; ** = p < .01; *** = p < .001

According to the household wealth model, the causal impact of living near a CBHF scheme is little to none. Across sub-populations, the there is no significant impact on the wealth index factor score or number of assets. In other words, the model informs us that living near a CBHF scheme does not have a significant impact on household wealth or assets. With regards to mosquito nets, I found that males in the treatment group do have a significantly higher number of mosquito nets. Males in the treatment group have 22.8% more mosquito nets than men living in the control group. This is still only a modest impact and not broadly indicative that units in the treatment group see household wealth increases. However, this continues with the trend from the last model in which males are the biggest beneficiaries of CBHF schemes.

Maternal Health Behavior Model

The maternal health behavior model is similar to the linear probability model we used earlier. Three out of the four outcome variables I test are dichotomous, and the DID coefficient tells us the increased probability of the outcome occurring for people in the treatment group. Of course, the primary difference for this model is that it focuses specifically on mothers and maternal health behaviors. Below are the four outcome variables I test using this model:

1. Currently using a contraceptive (dichotomous)
2. Visited health facility in past 12 months (dichotomous)
3. Weight (non-dichotomous)
4. Covered by health insurance (dichotomous)

Below, I report the results of my DID analysis for three sub-populations in the treatment and control groups: all mothers, poor mothers, and non-poor mothers. Once more, poor is defined as being below the 40^{th} percentile (or bottom two quintiles) of the DHS wealth index factor score.

All mothers

Maternal health, total Number of Observations	Currently using contraceptive 2232	Visited health facility in last 12 mo. 2232	Weight 2229	Covered by health insurance 2229
treatment	-0.041	0.001	-94.654**	0.001
	(0.03)	(0.03)	(34.04)	(0.02)
year	0.083**	0.278***	-3.436	0.087***
	(0.03)	(0.03)	(56.32)	(0.02)
treatment*year	0.185***	0.066	-0.916	0.051
	(0.04)	(0.04)	(72.73)	(0.03)
Age of respondent	-0.003	-0.013***	13.386***	0.002
	(0.00)	(0.00)	(3.15)	(0.00)
Age of respondent during 1st birth	0.010**	0.014***	-5.402	0.015***
	(0.00)	(0.00)	(4.37)	(0.00)
Yearss of education	0.030***	-0.002	-0.952	-0.020***
	(0.00)	(0.00)	(7.35)	(0.00)
Number of HH members	-0.009*	-0.013*	0.108	0.003
	(0.00)	(0.00)	(7.49)	(0.00)
Wealth index factor score	0.000***	-0.000	0.001***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Total children born	0.024***	0.032***	-26.649**	0.002
	(0.01)	(0.01)	(10.33)	(0.01)
Currently working	0.082***	-0.057***	3.345	0.035**
	(0.02)	(0.01)	(6.48)	(0.01)
Sex of HH head	-0.216***	0.059**	26.104	-0.027
	(0.02)	(0.02)	(40.47)	(0.02)
Constant	0.374***	0.649***	423.403**	-0.187**
	(0.09)	(0.09)	(139.39)	(0.06)

b / se. * = p < .05; ** = p < .01; *** = p < .001

Poor mothers

Maternal health, poor Number of Observations	Currently using contraceptive 924	Visited health facility in last 12 mo. 924	Weight 924	Covered by health insurance 924
treatment	0.042	-0.049	14.891	-0.030***
	-0.04	-0.04	-8.35	-0.01
year	-0.044	0.281***	11.069	0.108**
	-0.05	-0.05	-10.36	-0.04
treatment*year	0.246**	0.157*	-29.584	-0.143***
	(0.08)	(0.08)	(16.21)	(0.04)
Age of respondent	-0.005*	-0.013***	1.780**	-0.001
	(0.00)	(0.00)	(0.57)	(0.00)
Age of respondent during 1st birth	0.008	0.010	0.960	-0.002
	(0.01)	(0.01)	(1.19)	(0.00)
Yearss of education	0.038***	-0.012	-0.540	-0.009**
	(0.01)	(0.01)	(1.32)	(0.00)
Number of HH members	-0.020**	-0.041***	4.589**	0.006
	(0.01)	(0.01)	(1.49)	(0.00)
Wealth index factor score	0.000***	-0.000	0.000*	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Total children born	0.024***	0.037***	0.437	0.011
	(0.01)	(0.01)	(1.67)	(0.01)
Currently working	0.010	-0.086***	-20.308**	0.002
	(0.04)	(0.02)	(6.27)	(0.01)
Sex of HH head	-0.214***	0.077*	10.901	0.040
	(0.03)	(0.04)	(7.10)	(0.02)
Constant	0.917***	0.868***	490.938***	0.105
	(0.14)	(0.16)	(30.92)	(0.06)

b / se. * = p < .05; ** = p < .01; *** = p < .001

Non-poor mothers

Maternal health, non-poor Number of Observations	Currently using contraceptive 1308	Visited health facility in last 12 mo. 1308	Weight 1305	Covered by health insurance 1305
treatment	-0.066	0.016	-149.182*	0.034
	(0.04)	(0.04)	(58.92)	(0.03)
year	0.019	0.256***	29.831	0.101***
	(0.04)	(0.04)	(99.38)	(0.03)
treatment*year	0.248***	0.067	-45.753	0.032
	(0.05)	(0.05)	(107.45)	(0.04)
Age of respondent	-0.006**	-0.015***	24.588***	0.005*
	(0.00)	(0.00)	(6.14)	(0.00)
Age of respondent during 1st birth	0.014**	0.016***	-12.167	0.021***
	(0.00)	(0.00)	(6.80)	(0.00)
Yearss of education	0.009	0.006	6.483	-0.019***
	(0.01)	(0.01)	(12.66)	(0.00)
Number of HH members	-0.014**	0.002	1.809	0.003
	(0.01)	(0.01)	(11.69)	(0.01)
Wealth index factor score	0.000	-0.000	0.002*	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Total children born	0.055***	0.029**	-67.605**	-0.016
	(0.01)	(0.01)	(25.04)	(0.01)
Currently working	0.094***	-0.035*	11.064	0.059***
	(0.02)	(0.01)	(12.72)	(0.01)
Sex of HH head	-0.227***	0.052	52.490	-0.070**
	(0.03)	(0.03)	(62.40)	(0.02)
Constant	0.545***	0.537***	197.208	-0.342***
	(0.13)	(0.12)	(218.25)	(0.09)

b / se. * = p < .05; ** = p < .01; *** = p < .001

Among all mothers, the only outcome variable with a significant DID coefficient is "currently using contraceptive". Mothers living near a CBHF scheme have an 18.5% higher probability of currently using contraceptives (at the time of the 2014 survey) than mothers who don' t live near a CBHF scheme. Poor mothers are even bigger beneficiaries of CBHF schemes. Poor mothers in the treatment group are 24.6% more likely to be using contraceptives and 15.7% more likely to have visited a health facility in the past twelve months. It is very interesting to speculate why poor mothers are specific beneficiaries of AYI CBHF schemes, especially given the fact that the poor population in the other models were not specific beneficiaries of CBHF schemes. While it is outside the scope of this empirical paper to analyze the reasons poor mothers benefit from proximity to the AYI CBHF schemes, it perhaps has something to do with participant targeting or insurance package design.

VIII. Conclusion

Over the three difference-in-differences models I presented in this paper, I ran 40 separate tests on the impact of Afya Yetu Initiative's CBHF schemes in Kenya. Using the linear probability model on health behaviors, I found that proximity to CBHFs (i.e. assignment to the treatment group) increases the probability of health insurance enrollment and use of birth control. The impact is significantly higher for males, although it is still present for females. However, CBHF schemes have a significantly smaller, if any, impact on the poor.

Using the household wealth model, I found little evidence that proximity to CBHFs lead to household wealth. There was only one meaningfully causal result from this model: males who live near CBHF schemes have a significantly higher number of mosquito nets, but this number was relatively small. Thus, I found that proximity to CBHF schemes in Kenya don't lead to significant household increases in wealth.

Using the maternal health behaviors model, I found that proximity to CBHF schemes have a significant impact on contraceptive use for mothers. This impact was much higher for poor mothers. Additionally, poor mothers who live near a CBHF scheme are also more likely to have visited a health facility in the past twelve months. In sum, I tested forty impacts in total, of which thirteen (below) were significant in a way that supported my hypothesis that CBHI schemes create positive health behaviors. You can find results from these forty tests in Appendix III.

It is important to note that I measured average treatment effect, or the effect of the program on people assigned to the treatment group (even though there was much less than 100% compliance with treatment). In the context of my experiment, I tested the impact of CBHI schemes on people living within 5 kilometers of an AYI CBHF sublocation. In its 2015 evaluation, AYI reported that it only had an 11.91% penetration rate in communities with CBHF schemes (Oyaya et al., 2015). As such, it is likely that a large majority of people assigned to the treatment group were not direct participants of the program. These results, then, can be interpreted as indirect community-wide effects of CBHF schemes existing in the area, regardless of direct participation in the scheme itself. I have two takeaways from this.

First, the likely low level of compliance with receipt of treatment (i.e. participation of CBHF scheme) highlights that the impacts found in the DID analysis are essentially capturing the spillover effects from the program. While it is outside the scope of this paper to speculate why and how AYI's CBHF schemes generate these spillover effects on the community, it is important to recognize the existence of these indirect impacts on non-participants. The DID analysis presented in this paper contributes empirical evidence of spillover effects to the broader literature on CBHF schemes in developing countries.

The second takeaway from this analysis is that more experimental analysis on CBHF schemes is needed. I conducted this analysis using quasi-experimental difference-in-differences techniques, which has limitations. Apart from the parallel trends assumption, this DID analysis did not capture the effect of the treatment on the treated, or direct CBHF participants. While it is encouraging that spillover effects of the program exist, it would be meaningful to understand the impact of CBHF schemes on participants directly. There is room for a randomized control trial or other experimental technique to measure the direct impact of CBHF schemes on participants. An

RCT requires resources, planning, and stakeholder buy-in, but it is likely a worthy investment. The DID analysis presented in this paper found compelling average treatment effects of CBHF schemes on residents of program areas, but further empirical work is necessary to develop a consensus about the success of CBHF schemes in East Africa and around the world.

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APPENDIX I – Covariate Tests

Covariates: Linear probability model on health outcomes

Covariate	Model 1	Model 2	Model 3	Model 4
Age of respondent	0.006*	0.005***	0.004**	0.004
	(0.003)	(0.001)	(0.002)	(0.002)
Years of education	-0.023***	-0.020***	-0.021***	-0.022***
	(0.006)	(0.006)	(0.006)	(0.006)
Number of HH members	0.001			
	(0.005)			
Age of HH head	-0.001			
	(0.001)			
Literacy level	0.017		0.024	0.022
	(0.020)		(0.019)	(0.020)
Wealth index factor score (i.e. relative	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total children born	-0.014			
	(0.010)			
Currently working	0.053		0.067	0.059
	(0.045)		(0.043)	(0.044)
Currently married	0.045			0.040
	(0.050)			(0.044)
N	567.000	598.000	598.000	567.000
R-squared	0.231	0.220	0.223	0.229
Adj R-squared	0.215	0.212	0.212	0.216
AIC test	467.100	472.043	473.612	463.028
BIC test	523.525	502.798	513.155	506.431

Covariates: Expenditure model

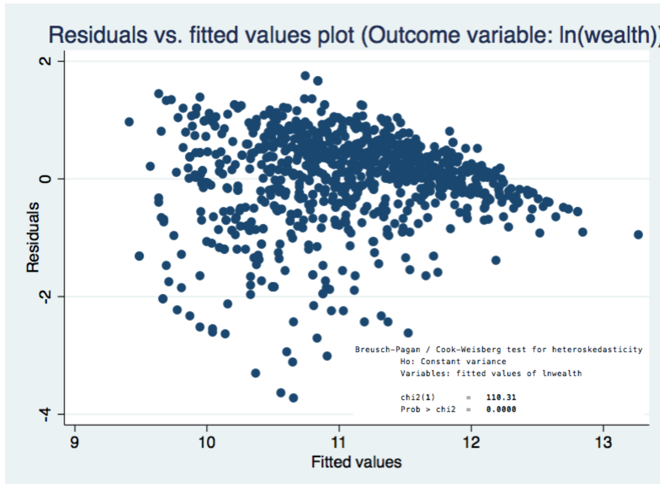
Covariate	Model 1	Model 2
Years of education	0.096**	0.088*
	(0.035)	(0.035)
Age of HH head	-0.011***	-0.011***
	(0.002)	(0.002)
Number of HH members	-0.077***	-0.084***
	(0.017)	(0.017)
Sex of HH head	0.218***	
	(0.062)	
Number of children under 5	0.116*	0.114*
	(0.046)	(0.047)
Owns bednet for sleeping	0.417***	0.417***
	(0.097)	(0.098)
N	899	899
R-squared	0.411	0.403
Adj R-squared	0.404	0.397
AIC test	2163.418	2173.715
BIC test	2221.034	2226.529

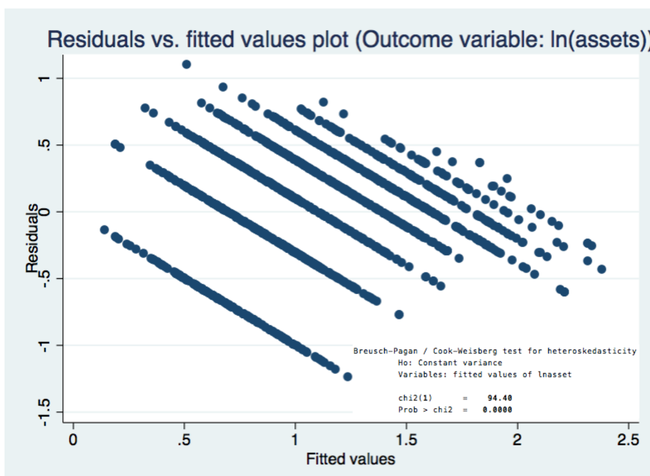
Covariates: Maternal health outcomes

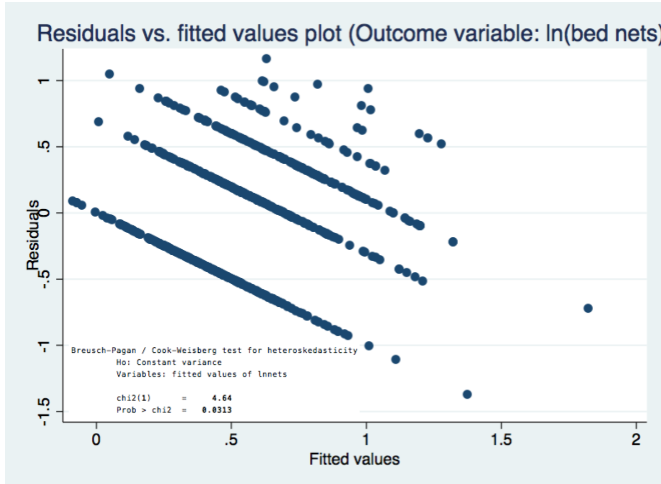
Covariate	Model 1	Model 2	Model 3	Model 4
Age of respondent	-0.003		0.002	0.002
	(0.002)		(0.001)	(0.001)
Age of respondent during 1st birth	0.010**	0.005	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Years of education	0.030***	0.028***	0.029***	0.029***
	(0.004)	(0.004)	(0.004)	(0.004)
Number of HH members	-0.009*			-0.001
	(0.005)			(0.004)
Wealth index factor score (i.e. relative	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total children born	0.024***			
	(0.006)			
Currently working	0.082***	0.084***	0.082***	0.082***
	(0.016)	(0.016)	(0.016)	(0.016)
Sex of HH head	-0.216***	-0.211***	-0.213***	-0.214***
	(0.022)	(0.022)	(0.022)	(0.022)
N	2232.000	2232.000	2232.000	2232.000
R-squared	0.163	0.157	0.157	0.157
Adj R-squared	0.159	0.154	0.154	0.154
AIC test	2858.901	2869.508	2869.706	2871.645
BIC test	2927.429	2920.904	2926.812	2934.462

APPENDIX II – Heteroscedasticity Tests

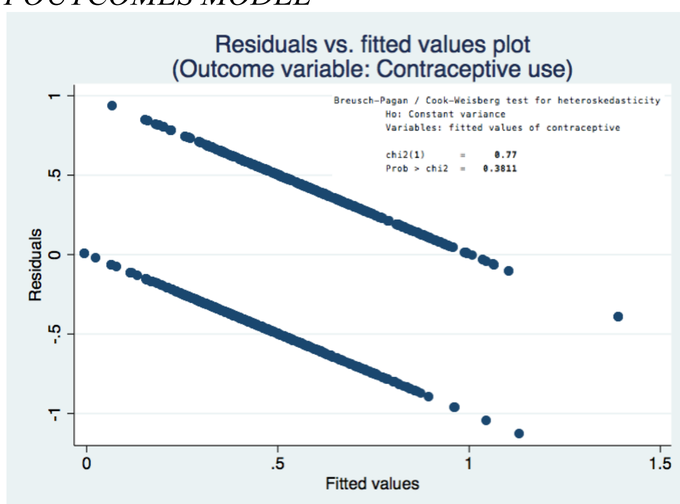
EXPENDITURE MODEL

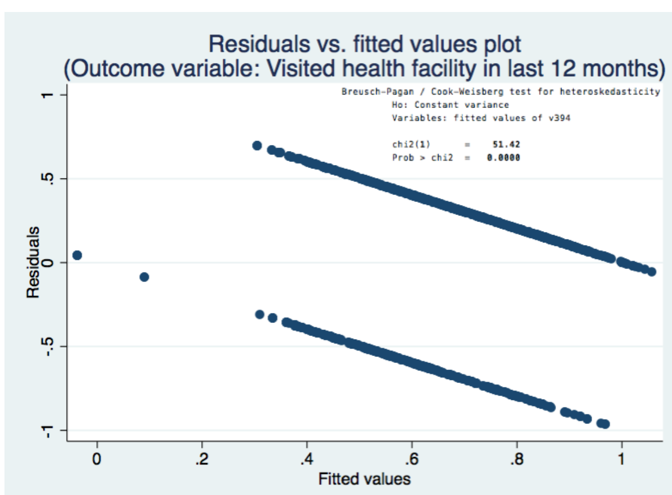


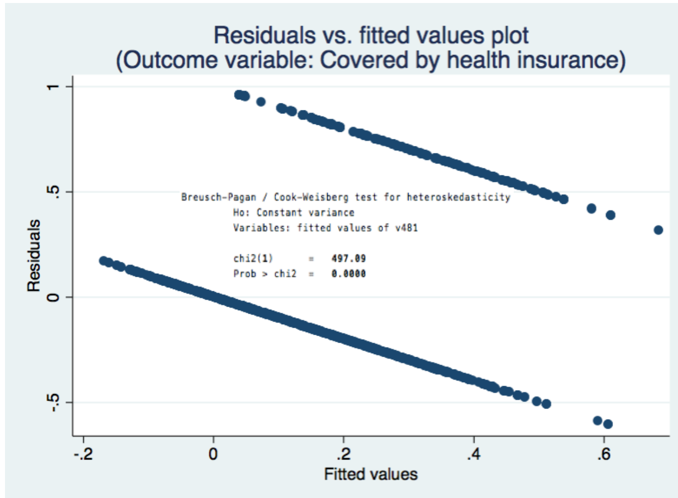


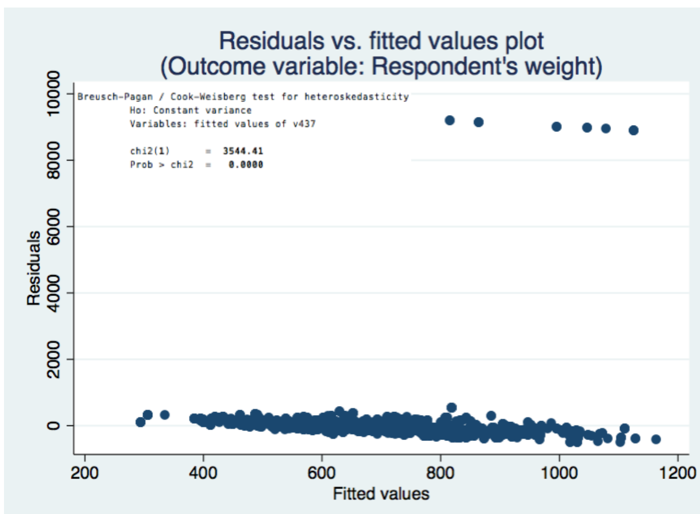


MATERNAL HEALTH OUTCOMES MODEL






Residuals vs. fitted values plot
(Outcome variable: Covered by health insurance)
Residuals
1
.5
0
-.5
-.2
0
.2
.4
.6
Fitted values
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of v481
chi2(1) = 497.09
Prob > chi2 = 0.0000


Residuals vs. fitted values plot
(Outcome variable: Respondent's weight)
Residuals
100000
80000
60000
40000
20000
0
200
400
600
800
1000
1200
Fitted values
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of v437
chi2(1) = 3544.41
Prob > chi2 = 0.0000

APPENDIX III – Summary of Results Tables

Model and population	Outcome variable	Significant at p < .05?	DID Coefficient
Model: Health behaviors Population: Total	Condom method used	No	n/a
	Been tested for AIDS	No	n/a
	Has health insurance	Yes	0.191
	Uses contraceptive	Yes	0.25
Model: Health behaviors Population: Poor	Condom method used	No	n/a
	Been tested for AIDS	No	n/a
	Has health insurance	No	n/a
	Uses contraceptive	Yes	0.173
Model: Health behaviors Population: Male	Condom method used	No	n/a
	Been tested for AIDS	No	n/a
	Has health insurance	Yes	0.31
	Uses contraceptive	Yes	0.403
Model: Health behaviors Population: Female	Condom method used	No	n/a
	Been tested for AIDS	No	n/a
	Has health insurance	Yes	0.095
	Uses contraceptive	Yes	0.145
Model: Household savings Population: Total	Wealth index factor score	No	n/a
	Number of assets	No	n/a
	Number of mosquito nets owned	Yes	0.189
Model: Household savings Population: Poor	Wealth index factor score	No	n/a
	Number of assets	No	n/a
	Number of mosquito nets owned	No	n/a
Model: Household savings Population: Male head of	Wealth index factor score	No	n/a
	Number of assets	No	n/a
	Number of mosquito nets owned	Yes	0.228
Model: Household savings Population: Female head	Wealth index factor score	No	n/a
	Number of assets	No	n/a
	Number of mosquito nets owned	No	n/a
Model: Maternal health Population: Total	Currently using contraceptive	Yes	0.185
	Visited health facility in last 12 months	No	n/a
	Weight	No	n/a
	Covered by health insurance	No	n/a
Model: Maternal health Population: Poor	Currently using contraceptive	Yes	0.246
	Visited health facility in last 12 months	Yes	0.157
	Weight	No	n/a
	Covered by health insurance	No	n/a
Model: Maternal health Population: Non-poor	Currently using contraceptive	Yes	0.248
	Visited health facility in last 12 months	No	n/a
	Weight	No	n/a
	Covered by health insurance	No	n/a