ESSAYS ON THE EFFECTS OF HEALTH INSURANCE AND EDUCATION ON CHILD HEALTH AND FERTILITY

by

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A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

My dissertation evaluates the effects of health and education reforms on child health and fertility. The first chapter examines the short and long run impacts of insurance on child health by exploiting the National Health Insurance Scheme (NHIS) in Ghana that was introduced in 2005. The reform was aimed at increasing access to health care by removing user fees. Using distance to the registration center as an instrument, I employ an instrumental variable strategy to evaluate the effects of the reform. My results in the first stage suggest that living closer to a registration center increases mother's probability of insurance. In the second stage, my results suggest that insurance affects child health in both the short and long runs. In the short run, insurance decreases 7-day and 1-month mortalities by 15 and 16 deaths per 1000 live births, respectively. In the long run, insurance decreases 1-year and 5-year mortalities by 44 and 88 deaths per 1000 live births, respectively. Following the reform, I also find improved health among children who survive. I find that children born after the reform are 23 and 8 percentage points less likely to be stunted and wasted, respectively. Examining possible pathways through which insurance affects health, I also find that insurance increases facility births, antenatal visits, and vaccination rates. Also, women with insurance sought early care during pregnancy and after delivery.

Health insurance can affect fertility positively or negatively. Fertility could increase if insurance decreases the cost of having a child, or fertility could decrease if parents believe that healthier children will grow old to take of them in their old age. Education, on the other hand, mainly decreases fertility. In the second chapter, co-authored with Sheila Afrakomah, we take advantage of the NHIS and an education reform, also introduced in Ghana in 2005, to estimate the effects of these concurrent programs on fertility. The Free Primary Education (FPE) removed school fees in public primary schools. We combine an instrumental variable and a difference-in-differences strategy based on the FPE and NHIS reforms in Ghana. We begin by separately estimating the effect of FPE and NHIS on fertility. We find that high exposure to FPE reduces the total number of births by 0.39 births and reduces the probability of first birth by 27 percentage points by age 25. FPE also increases the timing of first marriage by decreasing the likelihood of first marriage by 8 percentage points by age 25. However, women more exposed to NHIS have 0.94 more births and are 35 percentage points more likely to have their first child by age 25. The results from the separate estimations suggest that education reduces fertility whiles insurance increases fertility. Finally, we measure the effect of exposure to both reforms on fertility by using an instrumented difference-in-difference strategy. We find that the negative FPE effect on fertility lessens with increasing exposure to NHIS, while the positive NHIS effect on fertility is reinforced with increasing exposure to FPE.

Chapter 1

HEALTH INSURANCE AND CHILD: EVIDENCE FROM GHANA'S NATIONAL HEALTH INSURANCE SCHEME

1.1 Introduction

Despite progress made over the past 25 years, in 2017 alone, 6.3 million children and young adolescents (5.4 million under age 5) died from preventable diseases, with almost half of these in the first month of life (UN IGME, 2018). On current trends, 56 million children under the age of 5 are estimated to die between 2018 and 2030. Children born in Sub-Saharan Africa and Southern Asia are at a higher risk of dying before the age of 5, as four out of every five deaths of children occur in these regions. In acknowledging this problem and as part of Agenda 2030, the Sustainable Development Goals (SDGs) aim to reduce neonatal and under-5 mortalities to at least as low as 12 per 1000 live births and 25 per 1000 live births, respectively. To achieve this, many developing countries and global health organizations are pursuing policies aimed at increasing access to healthcare. Hence, the need to provide evidence on the efficacy of these policies to improve child health.

This paper evaluates the effect of increasing access to healthcare, through the elimination of user fees, on child health by examining the National Health Insurance Scheme (NHIS) in Ghana, introduced in 2005. I use data from the 2003, 2008, 2014 rounds of the Ghana Demographic and Health Survey (GDHS). The NHIS increases health insurance coverage, and using a two-stage least squares (2SLS) model, the additional insurance coverage generated by the policy reduces mortality, stunting (defined as having height-for-age z-score less than 2 standard deviations below the reference population mean) and wasting (defined as having weight-for-age z-score less than 2 standard deviations below the reference population mean).

Studies that examine the effects of policies aimed at increasing access to health, including health insurance policies, almost always focus on only the impact on healthcare utilization, and this evidence is quite mixed. Chankova et al. (2009) find that the National Health Insurance Scheme (NHIS) in Ghana had no impact on institutional deliveries between 2004 and 2007, whereas Singh et al. (2015) show that insurance coverage during pregnancy in Ghana was associated with greater use of facility delivery but not antenatal care (ANC).

Moreover, little robust evidence showing that healthcare use at birth lowers neonatal mortality (Chinkhumba et al., 2014) exists, and the evidence is mixed. Evaluating the Janani Suraksha Yojana (JSY) program aimed at increasing access to health care for pregnant women in India, Powell-Jackson et al. (2015) find an increase in the uptake of maternity services but no effect on neonatal mortality. Lim et al. (2010) on the other hand, find that the program significantly reduced neonatal mortality. The effect of health insurance on mortality has also been previously studied. For instance, while Currie and Gruber (1996a;1996b) and Chou et al., (2014) show that insurance reduced infant mortality in the US and Taiwan, respectively, Chen and Jin (2012) show that insurance had no effect on mortality in China. Friedman and Keats (2019) show that a policy to increase institutional births in Ghana had no impact on neonatal mortality but significantly increased vaccination rates, improved overall health and reduced long run mortality.

Given global child health priorities (AbouZahr 2003), the need to evaluate the impact of policies to reduce or eliminate user fees on child health can scarcely be exaggerated. Even though child health services are typically covered in health insurance benefit packages, only a few studies have used rigorous methodology, such as random control trial experiment, difference-in-differences, and instrumental variables (IV) to study the impact of health insurance on child health (Levy and Meltzer, 2008; Comfort et al. 2013). Existing studies do not always address issues of endogeneity, often focus on only one or two study areas within a given country, and thus are not generalizable (Comfort et al. 2013).

Unlike other studies that examine impacts of similar policies, I observe statistically significant effects on neonatal mortality. The policy decreased 7-day and 1-month mortalities by 15 and 16 deaths per 1000 live births, respectively. Predictably, long run mortality (1-year mortality and 5-year mortality) also improves, following the reform; 1-year and 5-year child mortalities decrease by 44 and 88 deaths per 1000 live births, respectively. I also find improved overall health, among children who survive, following the reform. I use height- and weight-for-age z-scores as summary measures of health. In comparison to children born before the policy, children born after the reform increase height by an additional 1.33 standard deviations and are 23 percentage points less likely to be stunted. Similarly, weight increases by an 0.65 additional standard deviations and children are 8 percentage points less likely to be wasted.

Investigating the pathways through which the increase in coverage improves child health can lead to a better understanding of household health decision-making process. The increase in coverage generated by the NHIS is found to increase facility births, antenatal visits, and vaccination rates for DPT (diphtheria, pertussis, and tetanus), BCG (which targets tuberculosis), and polio, and it leads to women seeking early care during pregnancy and post-delivery. The aggregate of these findings suggests that the timing of the first antenatal and postnatal visits, the number of antenatal visits, facility births, and the increase in BCG vaccination rates (administered at birth) are the main pathways through which the increase in coverage reduces neonatal mortality (i.e. 7-day and 1-month mortality). Additionally, for long-run child health (i.e. 1-year mortality, 5-year mortality, stunting and wasting), increase in vaccination rates for polio and DPT (the Ministry of Health recommends the first doses of polio and DPT at 6 weeks) are the main pathways through which the NHIS affects child health. Effect sizes of the reform range from an increase of 22 percentage points (BCG) to 33 percentage points (polio), depending on the vaccine.

All things considered, my results can help explain some of the earlier mixed evidence on the efficacy of the removal of user fees. First, my finding of a significant effect on neonatal mortality, like results of other studies (Lim et al., 2010; McKinnon et al., 2015), contrasts other studies (Ansah et al., 2009; Powell-Jackson et al., 2015; Friedman and Keats, 2019). One possibility for the contrasting results is perhaps the coverage of the policies analyzed. Friedman and Keats (2019) analyzed the Safe Motherhood Initiative, which allowed pregnant women in Ghana to deliver at either public or private facilities at no cost. That policy, unlike the NHIS, did not cover antenatal visits and postnatal visits. The NHIS is a more comprehensive program that covers not only facility births but also antenatal and postnatal care, and this could explain why I find positive impacts on neonatal mortality. I also find large impacts on overall health and longer-run child mortality, which is typically not addressed in previous studies. Friedman and Keats (2019), however, find similar effects. As potential mechanisms, this paper provides evidence of an increase in vaccination rates and antenatal visits. The proof of increased vaccination following the NHIS found in this paper, as well as evidence from Friedman and Keats (2019), supports this potential pathway.

My results add to the literature on increasing access to health by eliminating or significantly reducing user fees. A major concern is the effect of user fees on the demand for services and whether significantly decreasing user fees can stimulate the demand for health inputs among those who need it. My results suggest that user fees do affect demand and lead to reduced health and increased mortality. These results are consistent with policies that show that removing user fees increased demand for health use in India (Lim et al., 2010) and Zambia (Hangoma et al., 2018). This paper also finds evidence of a positive relationship between insurance and better child health and evaluates the detailed channels through which the connection develops. These results have huge policy implications and provides the much-needed evidence of the need for the government to continuously fund the program.

The remainder of the paper is as follows. Section 1.2 provides a history of healthcare in Ghana and the background of the policy. Section 1.3 explains the empirical strategy, sections 1.4 and 1.5 describe the sample characteristics in my data and explain the results, respectively. Finally, I conclude with a discussion in Section 1.6.

1.2 Historical context and background of the NHIS

The Republic of Ghana was the first country, south of the Sahara, to gain its independence from Britain, in 1957. Upon independence, Ghana implemented a system of free healthcare. However, economic deterioration in the mid-60's led to a gradual phase-in of user charges. By 1992, continued economic distress led the country to implement a system of full cost recovery (known as cash-and-carry), in which users were charged the full procurement cost for drugs and a partial cost for most services (Nyonator & Kutzin 1999). The objective was to generate revenues to cover at least 15% of total recurrent costs faced by the sector.

Unfortunately, the system of cash-and-carry posed a significant barrier to utilization of health services. In 1995, 56.6% of total health care expenditures were in the form of out-of-pocket payments. Consequently, patients changed their attitude towards seeking health care. A variety of studies found that patients often did not report illnesses to their health care providers and postponed purchasing drugs from pharmacies. In some cases, the costs of drugs were either spread among other household members or prescription drugs distributed within the household (Waddington & Enyimayew 1989; Waddington & Enyimayew 1990). By the late 1990s, user charges were recognized as a key national and political issue. Following years of out-of-pocket payment for healthcare, which negatively affected patient's attitude towards seeking health care (Waddington & Enyimayew 1990), Ghana introduced the National Health Insurance Scheme (NHIS) to provide access to affordable healthcare especially for the poor.

Prior to the NHIS, some districts in Ghana had community-based health insurance schemes (CBHI), also called Mutual Health Organizations (MHO), which required enrollees to pay annual premiums, ranging from $0.50 to $4. The MHO movement started in Ghana during the early 1990s with encouragement from the Ministry of Health and support from donors such as the Danish International Development Agency and the U.S. Agency for International Development (Atim 2000; Apoya and others 2001; Atim, Grey, and Apoya 2002; Aiken 2003). At the time the NHIS Act was passed, there existed 159 MHOs spread across 67 (of the 138) districts in all ten regions of the country (Atim, Grey, and Apoya, 2002). Some of the MHOs were districtwide, all residents of the district were eligible to enroll, while others were based on different types of collective groups, such as occupation, religion, or gender. As a result, most districts had little or no insurance coverage. Benefit packages also varied across MHOs. The MHOs covered less than 3% of the population nationwide, with the remainder depending on the cash-and-carry system.

While popular among members and international donors at the time, the MHOs were only targeted to specific areas, failed to address key social insurance issues, and were not supported by general government revenue to allow them to cater to the poor. Most importantly, with limited coverage, the system of user fees remained the predominant means of paying for health care. When the NHIS was introduced, existing MHOs were given the choice to either become part of a "district mutual health insurance" scheme, or pay nearly $600K to remain private, thus forcing almost all private schemes to merge.

In August 2003, the Government of Ghana passed the National Health Insurance Act and the NHIS became operational in March 2005. The Act established a district-based insurance system for each of the 138 districts in Ghana (218 districts exist currently) and linked them through a national insurance fund[1]. The Act mandates that all district schemes must charge an annual premium of roughly $8 per adult and exempt from premiums, those under 18, over 70, pensioners, deemed indigent, and since July 2008, all pregnant women (Mensah et al, 2010) [2].

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[1] In the year 2001, there were 110 districts in Ghana. By 2005, an additional 28 districts were created by splitting some of the original 110, bringing their number up to 138. In February 2008, there were more districts created which brought the number to 170. Since then, a further 46 districts have been added since 28 June 2012 bringing the total to 218 districts. Retrieved from: https://en.wikipedia.org/wiki/Districts_of_Ghana#cite_note-3. I use 110 districts in my study because at the time of the 2003 DHS survey, there existed 110 districts. Moreover, the new additions are just subdivisions of the original 110 districts.

[2] In 2005, per capita GDP was $491.94 and per capita household consumption expenditure was $473.58 (World Bank); exempt groups must still register to enjoy benefits. For children under 18, at least one parent must be registered to be allowed to register.

Under this scheme, maternal care benefits include four prenatal visits, delivery care and one postnatal visit; care for the child for up to three months post-delivery is included (Escobar et al, 2011; Dixon et al, 2014)[3]. There is no cost-sharing beyond the premiums - members do not pay any co-pays or deductibles (Nguyen et al, 2011). All formal sector employees and their dependents are automatically enrolled, and their premiums collected at the central level via payroll deductions. The Act mandates a predefined benefits package that covers 95% of the diseases in Ghana (Witter and Garshong, 2009; Nguyen et al, 2011). Services covered include outpatient consultations, essential drugs, inpatient care and shared accommodation, maternity care (normal and cesarean delivery), eye care, dental care, and emergency care. Excluded benefits include echocardiography, renal dialysis, heart & brain surgery, organ transplantation, and HIV retroviral drugs. In 2007, even with the program, less than 20% of the population had health insurance coverage. (Witter et al, 2007).

Beyond the premiums collected locally, the NHIS is financed through a National Health Insurance Levy, a 2.5% levy on goods and services collected under the Value Added Tax[4]. In addition, formal sector employees contribute 2.5% of their income to the NHIS (automatically diverted from their social security contributions). The NHIS was set up as a voluntary system because of the difficulties in targeting and mandating enrollment for the non-formal sector, to which nearly 80% of the population belong.

[3] Child is not required to be registered in the first three months to enjoy benefit.

[4] Premiums collected locally are forwarded to a central system, the National Health Insurance Authority

This problem is not unique to Ghana, most low-income countries have had great difficulties targeting the poor. All national health insurance systems in Africa, until 2003, were focused on a minority of easy-to-track subgroups, usually civil servants, and formal workers. The NHIS is the largest financier of health care in Ghana, with the country's total expenditure on health at 5.91% of GDP in 2015 (World Bank, 2017). Since its inception, NHIS coverage has expanded significantly: by the end of 2014, about 40% of the population was registered with the NHIS (World Bank, 2017).

Blanchet et al (2012), in evaluating the effect of the NHIS, found that women with health insurance are significantly more likely to seek formal health care when sick in Ghana. They examine the unconditional health behavior differential by simply comparing group averages of women currently enrolled in the NHIS and women not currently enrolled in the NHIS. To remove any bias and to identify conditional differences attributable to NHIS affiliation, they use propensity score matching. Nguyen et al (2011) also found that the policy has led to financial protection by significantly reducing the likelihood of incurring catastrophic payment, particularly among the poorest.

1.3 Empirical Strategy

The relationship between health insurance and child health can be estimated using ordinary least squares (OLS). However, if maternal insurance take-up is correlated with unobservable characteristics that also affect child health, the OLS estimates will be biased. The relationship could be overstated if mothers who are more likely to be insured are also more likely to invest in their children's health, leading to an upward bias of the OLS estimates. Alternatively, measurement error in insurance take-up could lead to a downward bias of the OLS estimate. For the OLS results, I estimate the equation given by

$$y_{ijt}= \alpha_0 + \alpha_1\, insured_{ijt} + X'_{ijt}\Gamma + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + u_{ijt} \tag{1.1}$$

The dependent variable y_{ijt} is variable of interest measuring various child health outcomes including height and weight-for-age z-scores, dummies for stunting, wasting, and mortality for child i in district j born in year t; $insured_{ijt}$ is the reported insurance status of the mother of child i in district j born in year t; $X'_{ijt}\Gamma$ is a vector of controls including child's place of residence, household income status, distance to closest health facility, and Free Primary Education (FPE), a concurrent program; δ_z is a set of survey year dummy variables because I use multiple waves of DHS; δ_j is a vector of district-specific fixed effects that capture any time-invariant characteristics of the different districts; δ_t is a set of birthyear-specific fixed effects that capture any cohort-specific effects on the health of the child, and $\delta_j \times trend_t$ is a set of district-specific linear trends that captures any changes over time within each district and u_{ijt} is the error term. Standard errors are clustered at the district level to allow for within-district correlation. α_1 captures the OLS estimates of the NHIS.

To address any endogeneity concerns, I use a two-stage least squares (2SLS) identification strategy by instrumenting maternal insurance take-up with mother's distance to the closest NHIS registration center after the policy is introduced.

Following the reform, people living closer to a registration center are more likely to be induced to take up insurance because of the lower traveling cost to a center. Distance, therefore, can be used to predict the probability an individual takes up insurance after the NHIS is introduced. The first stage is represented by the equation

$$insured_{ijt} = \beta_0 + \beta_1(distanceij \text{ x } post_t) + \beta_2 distance_{ij} + \beta_3 post_t + X'_{ijt}\Gamma + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + \varepsilon_{ijt} \quad (1.2)$$

The dependent variable, $insured_{ijt}$, the insurance take-up of the mother of child i in district j who gave birth in year t, is instrumented by $distance_{ij}$ x $post_t$; $post_t$ is a dummy variable equal to 1 for children born from 2005; $distance_{ij}$ is child i's mother's distance to the NHIS registration center in district j. The first stage estimate of β_1 can be interpreted as the effect of the NHIS on the mother's health insurance take-up. All other variables are defined as in equation 1.1.

The first-stage equation estimates the exogenous effect of the NHIS on maternal health insurance take-up. The predicted insurance take-up of the mother can then be used to find the causal effect between maternal insurance and child health in the second stage. The second stage equation can be defined as

$$y_{ijt} = \theta_0 + \theta_1 \widehat{insured}_{ijt} + \theta_2 distance_{ij} + \theta_3 post_t + X'_{ijt}\Gamma + \delta_j + \delta_t + \delta_j \times trend_t + v_{ijt} \quad (1.3)$$

The second stage uses the same set of controls as the first stage, and θ_1 captures the causal effect of the NHIS on child health exogenously generated by mother's distance to the closest NHIS registration center. Throughout this paper, the baseline specification uses all children under 5 in the sample including children born before the policy and include only the 2003 and 2008 rounds of the GDHS. However, for mortality analysis, I use the individual women dataset merged with the birth history dataset and include the 2014 round of the DHS. Standard errors are clustered at the district level to allow for within-district correlation.

The main assumption underlying the instrumental variable identification strategy is that the NHIS impacts child health only through maternal insurance take-up. This requires that concurrent changes in government policy not be correlated with maternal insurance take-up in the same way as the NHIS. The FPE policy, which could affect maternal insurance take-up, was introduced in the same year as the NHIS. The FPE was intended to increase access to basic education, which in the long run could affect child health (Currie and Moretti, 2003). To find the causal effect of the NHIS, I control for the FPE in the specifications above[5].

1.4 Data

Data come from the 2003, 2008 and 2014 Ghana Demographic and Health Surveys (GDHS), the National Health Insurance Authority (NHIA), and Ghana Statistical Service (GSS) made available through Integrated Public Use Microdata Series (IPUMS) International. In each cross section of the GDHS, data are collected from a nationally representative sample of women aged 15-49. The data collected contains information on demographic characteristics of women (e.g. age, education,

[5] To control for FPE, I use FPE district intensity levels computed in Afrakomah (2021).

asset ownership) as well as completed birth histories, including information on the month and year of all births and all child deaths that have occurred prior to the survey date. The GDHS also contains information on vaccinations, location of births, medical personnel present at birth and whether the child has had fever, a cough or diarrhea recently. Child anthropometric measurements (height and weight) are collected for all children under the age of 5 at the time of the survey. To analyze mortality, the GDHS data used are from merged individual women and birth history datasets; all other outcomes are analyzed using data from the under-5 dataset. The under-5 dataset also contains information on mothers including insurance take-up and years of schooling.

Data used to calculate distance (in kilometers) to closest NHIS registration center comes from the NHIA, which provides the geocode of the location of each center for each year, and the GDHS, which provides the geocode of each centroid in each survey year. I use the geocodes of the centroids and centers to find the distance of each centroid to each of the centers in the survey year, and then select the minimum distance as the distance of that cluster to the closest NHIS registration center.

1.4.1 Summary statistics

Figures 1.1a and 1.1b show that most mothers live within forty (40) kilometers of a registration center, using both the under-5 dataset and births history datasets. The under-5 dataset includes only births recorded in the five (5) years before each wave, whiles the births history dataset includes information on all children born to surveyed women. On average, mothers in both datasets live about twelve (12) kilometers away from the closest registration center, and the farthest a mother lives away from a center is about sixty-two (62) kilometers.

Sample characteristics for the GDHS data are presented in table 1.1. The table shows overall means of the various outcome variables, and separate means for children born before and after the policy. Neonatal mortality, measured as either deaths in the first 7 days or first month of life, are approximately 34 and 38 deaths per 1000 live births, respectively. Children born after the reform experience lower neonatal and long run mortalities. While all surviving children in the sample have height- and weight-for-age z-scores below the reference population mean, children born after the policy are 0.47 and 0.26 of a standard deviation taller and bigger, respectively. Unsurprisingly, children born after the policy are less likely to be stunted (defined as having a height-for-age z-score less than 2 standard deviations below the reference population mean) or wasted (defined as having a weight-for-age z-score less than 2 standard deviations below the reference population mean). All these provide suggestive evidence of the effect of the NHIS.

Table 1.2 shows the characteristics of insured and uninsured mothers in both datasets. Predictably, the table shows poor and less educated mothers are less likely to have insurance whiles mothers who live in urban areas are more likely to be insured.

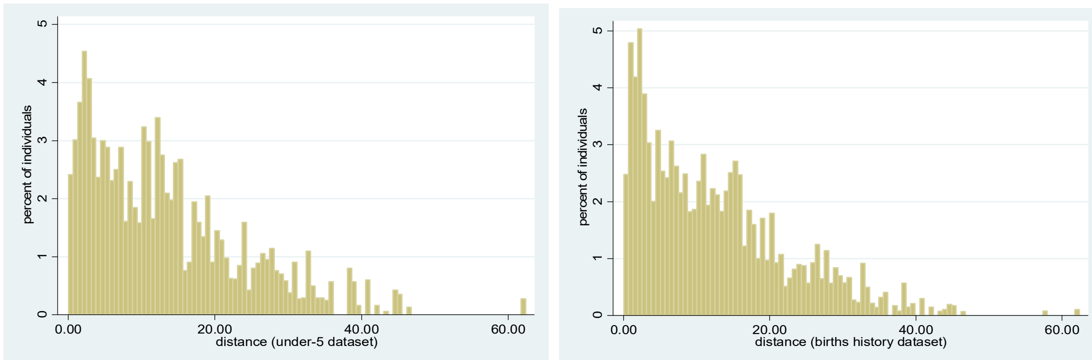

Figure 1.1(a and b): Histogram of distance to registration center.

Table 1.1: Child characteristics

	All Children (mean)	Children Born Before NHIS (mean)	Children Born After NHIS (mean)
Height-for-age z-score	-1.26	-1.42	-0.95
	(1.51)	(1.42)	(1.63)
Stunted	0.27	0.29	0.22
	(0.44)	(0.45)	(0.41)
Weight-for-age z-score	-0.90	-0.99	-0.71
	(1.21)	(1.16)	(1.30)
Wasted	0.15	0.16	0.13
	(0.36)	(0.37)	(0.34)
Mother insured	0.19	0.08	0.41
	(0.39)	(0.27)	(0.49)
N	**6,836**	**4,555**	**2,281**
Mortality per 1000 live births			
7-day mortality	33.62	35.74	27.88
	(180.25)	(185.65)	(164.64)
1-month mortality	37.86	40.56	30.55
	(190.85)	(197.27)	(172.09)
1-year mortality	75.03	82.95	53.62
	(263.44)	(275.82)	(225.28)
5-year mortality	103.68	118.26	64.27
	(304.85)	(322.92)	(245.24)
Mother insured	0.41	0.32	0.63
	(0.49)	(0.47)	(0.48)
N	**50,059**	**36,538**	**13,521**

Note: Standard deviations are in parenthesis. Analysis is based on 2003 and 2008 GDHS rounds. Mortality information, which also includes 2014 round of GDHS, is collected for all children born to surveyed women while other variables are collected for only children under 5.

Table 1.2: Mother characteristics

	Under-5 dataset			Births history dataset		
	All mothers (mean) (1)	Insured (mean) (2)	Uninsured (mean) (3)	All mothers (mean) (4)	Insured (mean) (5)	Uninsured (mean) (6)
Age	30.31	30.48	30.27	36.73	36.76	36.70
	(7.09)	(6.74)	(7.17)	(7.64)	(7.54)	(7.71)
Poor	0.55	0.43	0.58	0.54	0.51	0.56
	(0.50)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)
Non-poor	0.45	0.57	0.42	0.46	0.49	0.44
	(0.50)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)
Years of schooling	4.35	5.81	4.01	4.22	4.73	3.87
	(5.93)	(5.35)	(6.01)	(5.16)	(5.09)	(5.18)
Urban	0.30	0.42	0.27	0.35	0.41	0.31
	(0.46)	(0.49)	(0.44)	(0.48)	(0.49)	(0.46)
Rural	0.70	0.58	0.73	0.65	0.59	0.69
	(0.45)	(0.49)	(0.44)	(0.47)	(0.49)	(0.46)
N	6,836	1,300	5,536	50,059	20,316	29,743

Note: Standard deviations are in parenthesis. Analysis in columns 1,2 and 3 is based on data from 2003 and 2008 GDHS and include births recorded in the 5years before each wave. Analysis in columns 4, 5, and 6 is based on data from 2003, 2008 and 2014 waves and include information on all children born to surveyed women

1.5 Results

The first-stage results from columns 1 and 2 of table 1.3 show that mothers living closer to a registration center have a higher probability of insurance take-up. These results are similar when I use both the under-5 and the births history datasets. The results also show that, after the policy, maternal insurance take-up decreases by an additional 1.5 percentage point (using the under-5 dataset) and 2.3 percentage points (using the births history dataset) when distance increases by 1 kilometer. These are significant at 1 percent significance level.

Table 1.3: First stage results

Dependent variable	(1) Insured (under-5 dataset) IV first stage	(2) Insured (births history dataset) IV first stage
Distance x post	-0.015***	-0.023***
	(0.002)	(0.001)
Distance	-0.007***	-0.008***
	(0.001)	(0.001)
Mean	0.19	0.41
F-stat	29.37	7.46
N	6,836	50,059

Analysis in column (1) is based on data from 2003 and 2008 GDHS and include births recorded in the 5years before each wave. Analysis in column (2) is based on data from 2003, 2008 and 2014 waves and include information on all children born to surveyed women. F-stat is the joint significance of distance x *post and distance. Standard errors, clustered at the district level, are in parenthesis.*
**** p<0.01, ** p<0.05, * p<0.1*

I estimate the effect of the NHIS on neonatal mortality, measured by 7-day and 1-month mortality rates. I estimate equation 1.1 using the reported maternal insurance take-up from the data, not the predicted take-up from the first stage. The OLS estimates are reported in columns 1 and 3 of table 1.4. The OLS estimates show no impact of the policy on neonatal mortality, and this is surprising because wealthier and more educated mothers are more likely to have insurance. However, these estimates do not describe a causal relationship between insurance and neonatal mortality because unobserved characteristics that affect maternal insurance also affect neonatal mortality.

To address this issue, an IV strategy is used to measure the effect of this increase in insurance take-up on neonatal mortality. Estimating the second stage equation of the 2SLS model, equation 1.3, focuses on the relationship between the predicted level of maternal insurance take-up and neonatal mortality. I find statistically significant effects on neonatal mortality measured as either deaths in the first seven (7) days, or first month, unlike some studies (Ansah et al., 2009; Powell-Jackson et al., 2015; Friedman and Keats, 2019) that examine the effects of removing user fees to increase access to health. Relative to studies that find effects on neonatal mortality, I find much larger impacts. Lim et al., (2010), analyzing the JSY program in India aimed at incentivizing women to give birth in a health facility, find a decrease in 7-day and 1-month mortalities by 4.1 and 2.4 deaths per 1000 live births, respectively. McKinnon et al., (2015) found similar effects in Ghana, Senegal, and Kenya when they analyzed similar policies that reduced user fees. They find a decrease in 1-month mortality by 2.9 neonatal deaths, on average, per 1000 live births. Prior to the NHIS, the rates of 7-day and 1-month mortality were approximately 36 and 41 per 1000 live births. The results in columns 2 and 4 of table 1.4 show that the exogenous increase in insurance take-up generated by the NHIS decreased 7-day mortality and 1-month mortality by 15 and 16 deaths per 1000 live births, respectively. These estimates are statistically significant at the 1 percent significance level. One possible explanation for the difference in magnitude could be the comprehensive coverage of the NHIS, compared to policies aimed at just eliminating user fees at birth. The NHIS benefits include four prenatal visits, delivery care, and one postnatal visit.

Table 1.4: Effect of NHIS on neonatal mortality (deaths per 1000 live births)

	(1)	(2)	(3)	(4)
Dependent variable	7-day mortality		1-month mortality	
	OLS	IV 2nd stage	OLS	IV 2nd stage
Insured	0.50	-15.36***	0.30	-16.10***
	(2.00)	(5.71)	(2.20)	(5.50)
Pre-reform mean	35.74	35.74	40.56	40.56
Weak IV Robust statistic		7.65		8.89
		[0.007]		[0.004]
Number of clusters	110	110	110	110
N	50,059	50,059	50,059	50,059

*Data are from 2003, 2008 and 2014 GDHS and include historical births of all surveyed women. All dependent variables are binary, an indicator that equals 1 if true. Standard errors, clustered at the district level, are in parenthesis. Anderson and Rubin (1949) test statistic of the 2SLS estimate are shown along with the p-value from associated Wald test, given in square brackets. Birthyear-specific fixed effects, district-specific fixed effect and district-specific linear trends are included in all regressions. *** p<0.01, ** p<0.05, * p<0.1*

Next, I investigate the effect of the NHIS on long run mortality, measured by 1-year and 5-year mortality rates, and report the results in table 1.5. The OLS estimates, derived by estimating equation 1.1, are reported in columns 1 and 3. The estimates show that the NHIS had no significant impact on 1-year mortality but reduced 5-year mortality by 9 deaths per 1000 live births. These estimates do not describe causal relationship, and so I estimate a 2SLS, equations 1.2 and 1.3. Like Friedman and Keats (2019), I find a positive impact on long run mortality. The 2SLS estimates, reported in columns 2 and 4, show that the NHIS decreased 1-year and 5-year mortality rates by 44 and 88 deaths per 1000 live births, respectively. These estimates are significant at the 1 percent significance level. My estimates are larger than what Friedman and Keats (2019) find in Ghana. They find 12-month and 36-month mortalities drop by 21 and 44 deaths per 1000 live births, respectively. The difference in magnitudes shows the importance of care before and after delivery, given they analyze a policy that eliminates user fees only at delivery. Under the NHIS, a child below 18 is exempted from paying premiums, suggesting that this could positively affect health-seeking behavior even after birth.

Table 1.5: Effect of NHIS on long run mortality (per 1000 live births)

	(1)	(2)	(3)	(4)
Dependent variable	1-year mortality		5-year mortality	
	OLS	IV 2nd stage	OLS	IV 2nd stage
Insured	-5.05	-44.44***	-9.85**	-88.28***
	(3.33)	(8.93)	(4.01)	(11.78)
Pre-reform mean	82.95	82.95	118.26	118.26
Weak IV Robust statistic		26.73		68.98
		[0.000]		[0.000]
Number of clusters	110	110	110	110
N	50,059	50,059	50,059	50,059

Data are from 2003, 2008 and 2014 GDHS and include historical births of all surveyed women. All dependent variables are binary, an indicator that equals 1 if true. Standard errors, clustered at the district level, are in parenthesis. Anderson and Rubin (1949) test statistic of the 2SLS estimate are shown along with the p-value from associated Wald test, given in square brackets. Birthyear-specific fixed effects, district-specific fixed effect and district-specific linear trends are included in all regressions.
**** p<0.01, ** p<0.05, * p<0.1*

Finally, among children who survive, I estimate the effect of NHIS on their overall health, measured by stunting and wasting, which previous research rarely studies. Prior to the reform, the average weight- and height-for-age z-scores were -0.99 and -1.42, respectively. The OLS estimates in columns 1 and 3 of table 1.6, which do not describe a causal relationship, show that children born after the policy are 0.34

standard deviations taller and 7 percentage points less likely to be stunted (defined as having height-for-age z-score less than 2 standard deviations below the reference mean). The 2SLS estimates, which describe a causal relationship, in columns 2 and 4 of table 1.6 show an increase in height-or-age z-score by 1.33 standard deviations and a reduction in the probability a child is stunted by 23 percentage points. These are statistically significant at the 1 percent level. Additionally, the probability a child is wasted (defined as having weight-for-age z-score less than 2 standard deviations below the reference mean) decreases by 7 percentage points as the weight-for-age z-scores increases by 0.65 of a standard deviation. These are reported in columns 2 and 4 of table 1.7. These estimates are bigger in relation to what existing literature finds.

Table 1.6: Effect of NHIS on stunting

	(1)	(2)	(3)	(4)
Dependent variable	Height-for-age z-scores		Stunted	
	OLS	IV 2nd stage	OLS	IV 2nd stage
Insured	0.34***	1.33***	-0.07***	-0.23***
	(0.07)	(0.24)	(0.02)	(0.06)
Pre-reform mean	-1.42	-1.42	0.29	0.29
Weak IV Robust statistic		32.81		15.33
		[0.000]		[0.000]
Number of clusters	110	110	110	110
N	6,836	6,836	6,836	6,836

Data are from 2003 and 2008 GDHS and include births recorded in the 5years before each wave. Dependent variables in columns 3 and 4 are binary, an indicator that equals 1 if true. Standard errors, clustered at the district level, are in parenthesis. Anderson and Rubin (1949) test statistic of the 2SLS estimate are shown along with the p-value from associated Wald test, given in square brackets. Birthyear-specific fixed effects, district-specific fixed effect and district-specific linear trends are included in all regressions.
**** p<0.01, ** p<0.05, * p<0.1*

Table 1.7: Effect of NHIS on wasting

	(1)	(2)	(3)	(4)
Dependent variable	Weight-for-age z-scores		Wasted	
	OLS	IV 2nd stage	OLS	IV 2nd stage
Insured	0.24***	0.65***	-0.05***	-0.08*
	(0.05)	(0.17)	(0.01)	(0.04)
Pre-reform mean	-0.99	-0.99	0.16	0.16
Weak IV Robust statistic		14.96		3.39
		[0.000]		[0.068]
Number of clusters	110	110	110	110
N	6,836	6,836	6,836	6,836

*Data are from 2003 and 2008 GDHS and include births recorded in the 5years before each wave. Dependent variables in columns 3 and 4 are binary, an indicator that equals 1 if true. Standard errors, clustered at the district level, are in parenthesis. Anderson and Rubin (1949) test statistic of the 2SLS estimate are shown along with the p-value from associated Wald test, given in square brackets. Birthyear-specific fixed effects, district-specific fixed effect and district-specific linear trends are included in all regressions. *** p<0.01, ** p<0.05, * p<0.1*

1.5.1 Mechanisms

In this section, I explore possible pathways through which the NHIS could affect child health and report the results in table 1.8. I estimate equations 1.2 and 1.3 and find large impacts of the NHIS on early health care, proxied by vaccination rates, institutional delivery, and timings of the first antenatal and postnatal visits. These large estimates could explain the effect size of the NHIS on mortality, stunting and wasting that I observed above. After the policy was implemented, vaccination rates for DPT (diphtheria, pertussis, and tetanus), BCG (which prevents tuberculosis), and polio increased by 22-33 percentage points. These improvements suggest an increased contact with health professionals after delivery, because except for BCG, these vaccines are not administered at birth. The first doses of polio and DPT are usually at 6 weeks, per the recommendation from Ghana's Ministry of Health. From column 1 of table 1.8, facility births increased by 30 percentage points, following the reform, compared to Friedman and Keats (2019), who observed an increase in facility births by 8.6 percentage points. McKinnon et al. (2015), also studying reforms that eliminate user fees in Ghana, Senegal, and Kenya, found an increase in facility births by an average of 3.1 percentage points. Once more, the large effect of the NHIS on facility births could be driving the main results observed in this paper. However, my estimate is lower compared to the 45 percentage points increase in facility births Lim et al. (2010) find in India.

The World Health Organization (2018) recommends pregnant women have a minimum of 8 contacts with a health professional during each pregnancy, with the first contact occurring within the first trimester. Prior to the reform, the average number of antenatal visits was 3 per pregnancy. The NHIS increases the probability of having the first antenatal visit withing the first trimester by 46 percentage points and increases the number of antenatal visits by 4, as reported in columns 6 and 8, respectively. These are significant at 1 percent significance level. Additionally, from column 7, the NHIS increases the probability of the child's first postnatal contact with a health professional by 19 percentage points, and this is statistically significant at 10 percent. These could be critical pathways through which insurance affects health and explain the large estimates of the effect of the NHIS, because unlike other reforms, the NHIS covers antenatal and postnatal care. Additionally, these could also explain the large increase in facility births as Gabrysch and Campbell (2009) observed in low- and middle-income countries.

Table 1.8: Effect of NHIS on early child care

	(1) Facility Birth	(2) BCG vaccine	(3) Polio vaccine	(4) Measles vaccine	(5) DPT vaccine	(6) First antenatal within 3 months	(7) First postnatal within 2 months	(8) Number of antenatal visits
Insured	0.30***	0.22***	0.33***	0.02	0.32***	0.46***	0.19*	4.162***
	(0.06)	(0.05)	(0.08)	(0.06)	(0.09)	(0.08)	(0.11)	(0.69)
Pre-reform mean	0.43	0.79	0.35	0.66	0.64	0.31	0.23	3.44
N	6,836	6,836	6,836	6,836	6,836	6,836	6,836	6,836

*Data are from 2003 and 2008 GDHS and include births recorded in the 5years before each wave. Dependent variables in columns 1-7 are binary, an indicator that equals 1 if true. Standard errors, clustered at the district level, are in parenthesis. Birthyear-specific fixed effects, district-specific fixed effect and district-specific linear trends are included in all regressions. *** p<0.01, ** p<0.05, * p<0.1*

1.5.2 Robustness

Tables 1.9 and 1.10 report specification checks using variations of equations 1.2 and 1.3. Column 2 in each table limits controls to only birth-year and district fixed effects, and district-specific linear trends, excluding individual-level controls. The results are robust to the exclusion of individual-level controls. In column 3 of table 1.9, I limit my analysis to only children born 10 years before and after the policy, with all controls included, and still find the baseline results robust to this limited sample[6]. For stunting and wasting, because of data availability, I limit my sample to children born 4 years before and after the policy, and still find significant results[7].

[6] The youngest child in the births history sample was born in 2014, which is 10 years (including 2005) after the policy was introduced.

[7] The youngest child in the under-5 sample was born in 2008, which is 4 years (including 2005) after the policy was introduced.

Table 1.9: Specification checks – child mortality (per 1000 live births)

	(1) Baseline (equation 1.3)	(2) Exclude controls	(3) Kids born ten years before/after policy
Dependent variable: 7-day mortality			
$\widehat{Insured}$	-15.36***	-15.50***	-12.90**
	(5.71)	(5.70)	(5.25)
N	50,059	50,059	33,760
Dependent variable: 1-month mortality			
$\widehat{Insured}$	-16.10***	-16.30***	-13.40***
	(5.50)	(5.48)	(5.03)
N	50,059	50,059	33,760
Dependent variable: 1-year mortality			
$\widehat{Insured}$	-44.44***	-44.60***	-37.40***
	(8.93)	(8.90)	(8.05)
N	50,059	50,059	33,760
Dependent variable: 5-year mortality			
$\widehat{Insured}$	-88.28***	-88.20***	-70.00***
	(11.78)	(11.70)	(9.73)
N	50,059	50,059	33,760

*Data are from 2003, 2008 and 2014 GDHS. Standard errors, clustered at the district level, are in parenthesis. Analysis in column 3 includes only children born before 10 years before and after the NHIS. *** p<0.01, ** p<0.05, * p<0.1*

Table 1.10: Specification checks – stunting and wasting

	(1) Baseline (equation 1.3)	(2) Exclude controls	(3) Kids born four years before/after
Dependent variable: Stunted			
$\widehat{\text{Insured}}$	-0.23***	-0.24***	-0.19***
	(0.06)	(0.06)	(0.07)
N	6,836	6,836	5,112
Dependent variable: Wasted			
$\widehat{\text{Insured}}$	-0.08*	-0.08*	-0.10**
	(0.04)	(0.04)	(0.04)
N	6,836	6,836	5,112

*Data are from 2003 and 2008 GDHS. Standard errors, clustered at the district level, are in parenthesis. Analysis in column 3 includes only children born 10 years before and after the NHIS. *** p<0.01, ** p<0.05, * p<0.1*

Finally, I use my IV specification to address any alternative explanations for my results. I check whether the characteristics of mothers changed following the policy. In table 1.11, I present results of estimating equations 1.2 and 1.3 on a set of mother characteristics and find no change in the composition of mothers that were induced to take-up insurance following the reform. These results strongly indicate that the IV estimates describe a causal impact of the NHIS on child health.

Table 1.11: IV on mother characteristics

Dependent variable	(1) Poor	(2) Rural	(3) Births last 5 years	(4) Pregnant
$\widehat{\text{Insured}}$	0.07	-0.09	0.20	-0.05
	(0.07)	(0.08)	(0.13)	(0.04)
N	6,836	6,836	6,836	6,836

*Data are from 2003 and 2008 GDHS. Standard errors, clustered at the district level, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

1.6 Conclusion

In this paper, I estimate the causal effect of health insurance on child health using a 2SLS estimation strategy. The first stage results show that the NHIS significantly increased maternal insurance take-up. My estimates show that the NHIS increased insurance take-up by 1.5 (using the under-5 datasets) and 2.3 (using the births history datasets) percentage points. Additionally, the second stage estimates show, following the reform, the probability of wasting and stunting decreased by 8 and 23 percentage points, respectively, and 5-year mortality decreased by 88 deaths per 1000 live births. I also find a positive impact on healthcare utilization, implying that user fees negatively affect health-seeking behavior. This supports evidence from studies in developing countries that cost is a significant barrier to healthcare use (Gabrysch and Campbell, 2009; Richard et al., 2010).

A major contribution of this paper is the effect on neonatal mortality. I find a decrease in 7-day and 1-month mortality by 15 and 16 deaths per 1000 live births, respectively. Several studies have suggested that increased healthcare utilization may not necessarily lead to better health outcomes and have encouraged further studies to evaluate effect on mortality (De Allegri et al., 2012; Dzakpasu et al., 2014). In fact, a randomized controlled trial in Ghana found that removing out-of-pocket costs increased utilization but had no impact of mortality (Ansah et al., 2009). Therefore, the effect of the NHIS estimated in this paper, especially on neonatal mortality, is an encouraging finding and an important contribution to the literature, which could be explained by the comprehensive coverage of the NHIS. The existing literature rarely measures effects of reforms on overall health. In this paper, I also estimate the effect of the NHIS on overall health, measured by stunting and wasting.

One concern about the implementation of the NHIS is that the rapid increase in insurance take-up could overwhelm the weak health facilities, leading to little or no effect on health outcomes. In contradiction to such concerns, my results provide a strong evidence that the NHIS was not only effective in improving short run child health outcomes but also had long term effects. These are important findings because increased access to health insurance is a policy tool that can be used to improve child health outcomes in developing countries.

Chapter 2

EDUCATION AND HEALTH: THE IMPACT OF FREE PRIMARY EDUCATION AND HEALTH INSURANCE ON FERTILITY. EVIDENCE FROM GHANA

Richard Takyi Amoah and Sheila Afrakomah

2.1 Introduction

Fertility is important for economic growth. The reduction in fertility creates the potential for a demographic dividend and economic growth. A decline in fertility leads to an increase in income levels, due to the rise in working-age share of the population and fall in youth dependency rates (Karra et. al., 2017). Lower fertility could also generate higher participation rates in the labor force, especially for women and lead to greater investment in the health and education of each child, thereby increasing human capital (Karra et. al., 2017; Bloom et. al., 2009).

Fertility rates, however, tend to be higher in developing countries. In sub-Saharan Africa, the total fertility rate stands at 4.7 births per woman, which is more than twice the level of any other world region (United Nations, 2019). According to Nargund (2009), fertility rates are higher in these countries due to generally lower levels of female education and the lack of access to contraceptives. Hence, women's education and health programs are vital in determining the rate of fertility. Over the past few years, many developing countries and international development organizations have pursued policies and interventions aimed at increasing access to education and healthcare to develop human capital. A large literature has studied the separate effects of education or health reforms on fertility in sub-Saharan Africa and a negative relationship is generally observed between education and fertility (e.g. Chicoine, 2012; Chicoine, 2020; Zenebe Gebre, 2020). Health, on the other hand, can affect fertility positively (Abrokwah et al., 2016) or negatively (Troland and Figinski, 2019). While these studies separately observe a negative effect of education on fertility and a mixed relationship between health policies and fertility, the extent to which concurrent health and education policies affect fertility is unknown. We examine whether a concurrent health (education) policy could reinforce or lessen the effect of education (health) on fertility.

In this paper, we evaluate the returns to nationwide health insurance and free schooling programs in Ghana. We use data from the Ghanaian census and four rounds of the Demographic and Health Survey (DHS). In 2005, Ghana introduced free primary education (FPE) and the national health insurance scheme (NHIS). The FPE policy abolished school fees in public primary schools, while the NHIS removed healthcare user fees. The empirical strategy is an instrumented triple difference that uses three sources of variation. We use the geographic variation in the pre-FPE school dropout rate and variations in the cohort exposure to the policy, combined with the spatial variation in the distance to a NHIS registration center. Specifically, to identify the FPE effect, we exploit the idea that the degree of impact in each district will correspond to the district and cohort-specific dropout rate, prior to the policy. The abolition of fees would have a greater impact in districts with higher dropout rates, since more children could be induced to stay in school and complete primary education, and a lower impact in districts with low dropout rates. We combine this geographic and cohort variation in the exposure to the FPE with the spatial variation in distance to a NHIS registration center. This empirical strategy allows us to study whether the effect (slope) of FPE on fertility changes if exposure to NHIS changes. It also allows us to estimate whether the effect (slope) of NHIS on fertility changes if exposure to FPE changes.

We begin by separately estimating the effect of FPE and NHIS on fertility. We find that high exposure to FPE reduces the total number of births by 0.39 births and reduces the probability of first birth by 27 percentage points by age 25. FPE also increases the timing of first marriage by decreasing the likelihood of first marriage by 8 percentage points by age 25. Women exposed to NHIS have 0.94 more births and are 35 percentage points more likely to have their first child by age 25. Finally, we measure the effect of exposure to both reforms on fertility. We find that the FPE effect on fertility lessens with increasing exposure to NHIS, while the NHIS effect on fertility is reinforced with increasing exposure to FPE.

Earlier literature has documented the separate effects of education (Kravdal, 2002; Breierova and Duflo, 2004; Brand and Davis, 2011; Chicoine, 2012; Cygan-Rehm and Maeder, 2012) and health insurance (Winegarden and Murray, 2004; Schmidt, 2007) on fertility that exist in the data. In Africa, a negative causal relationship between education and fertility is predominantly observed but the evidence in other settings is mixed. To estimate the effect of education, Keats (2018) exploited age discontinuity in exposure to FPE in Uganda, Chicoine (2021) used a two-stage least squares model to estimate the effect of the FPE in Ethiopia, and Zenebe Gebre (2020) used a difference-in-difference strategy to estimate the effect of the FPE in Malawi. All papers found that education led to a decrease in fertility by 0.36, 0.44 and 0.28 (through the age of 25) births for each additional year of school, respectively. Additionally, Ali and Gurmu (2018) also found that female education significantly reduces the number of births per woman in Egypt. Even though these articles found similar results, the pathways vary. For example, Chicoine (2020) did not find any effect on contraception use but Keats (2018) and Zenebe Gebre (2020) found evidence of increased use of contraception.

Studying a reform in Norway that increased the number of years of compulsory schooling from seven to nine years and was implemented over a 12-year period from 1960 to 1972 in different municipalities at different times, and exploiting the spatial and temporal variations, Monstad et al., 2008 found no causal relationship between education and fertility. Similarly, using discontinuities at starting ages, McCrary and Royer (2011) found no evidence that school entry policies affect the probability of motherhood or age at first birth. In Taiwan, Kan and Lee (2018) used a regression discontinuity design and found no effect of female education on fertility. Fort et al. (2016) found a negative relationship between education and fertility in England but did not find a similar relationship in continental Europe.

The effect of health insurance on fertility is not straightforward, because the effect could be positive or negative. In developing countries, children are needed as a labor force and to provide care for their parents in old age. Therefore, fertility may decrease if children are more likely to survive into adulthood (quality-quantity tradeoff). But fertility may also increase if insurance lowers the cost of having a child. The evidence is quite mixed. Using a trend break specification with county-level variation in insurance, Troland and Figinski (2019) found evidence of the quality-quantity tradeoff as fertility declined. Apostolova-Mihaylova and Yelowitz (2018) find no effect of insurance, on net, on fertility. However, they find insurance increased fertility by 1 percent for married women and decreased fertility by 9 percent for unmarried women. According to Zavodny and Bitler (2010), Medicaid expansions were not significantly associated with a change in overall fertility. In Ghana, Abrokwah et al. (2016) found that the NHIS led to an increase in fertility around the time the program was implemented in 2005 but found no evidence in more recent data.

The results of this paper are significant because they provide evidence of whether the effect of education or health policy on fertility are reinforced or lessened by the other. Most developing countries over the years have introduced reforms aimed at improving access to education and health, and it is imperative to provide evidence as to whether these policies complement each other or not.

2.2 Background of FPE and NHIS

2.2.1 Free Primary Education in Ghana (The Capitation Grant Scheme)

Prior to 2005, Ghana practiced a cost-sharing scheme in its educational system. Under the cost-sharing scheme, the government and parents each absorbed a portion of a child's primary education. The government covered tuition, provided textbooks, and teaching and learning materials, and also subsidized the cost of exercise books, while parents bore the other costs of their children's primary education (HIPC WATCH, 2009). Moreover, parents were also required by schools to pay levies to district Assemblies as a means of raising funds for school repairs, cultural and sporting activities (HIPC WATCH, 2009). The indirect costs and levies constituted a significant share of households' income and acted as a barrier to education access (World Bank, 2010). In 2005, the government of Ghana completely abolished all forms of school fees in all public schools in Ghana effective at the start of the 2005/2006 school year. Under this policy, schools were given a Capitation Grant (CG) for each pupil enrolled to cover the previously collected fees and levies. Schools received an amount GH¢3.00

(approximately $2.10) per student to replace the lost revenue from the total abolishment of school fees.

2.2.2 The National Health Insurance Scheme

In 2005, Ghana introduced the National Health Insurance Scheme (NHIS) to replace the cash-and-carry system, which required out-of-pocket payments when seeking health care. The NHIS removed health care user fees, which earlier studies had shown negatively affected the utilization of healthcare (Waddington & Enyimayew 1989; Waddington & Enyimayew 1990). Members are required to pay an annual premium of about $8 per adult, and all Social Security and National Insurance Trust (SSNIT) contributors are automatically enrolled. Individuals over 70, under 18, considered indigent, and pensioners are exempt from paying premiums. Additionally, since July 2008, to promote reproductive and maternal health services, all pregnant women are exempt from paying premiums (Mensah et al, 2010). There are no deductibles or co-pays beyond the premiums (Nguyen et al, 2011).

The scheme has a pre-defined benefit package of about 95% of the most common diseases seen at health care facilities in Ghana (Witter and Garshong, 2009; Nguyen et al, 2011). The services covered include general outpatient and in-patient care, reproductive and maternal care (normal and caesarean delivery). Nonetheless, expensive procedures such as dialysis for chronic renal failure, cancer treatments, and cosmetic surgeries are not covered. The scheme has many funding sources with taxes making up about 90% of total annual inflows. The sources of funding include a 2.5% value added tax levied on selected goods and services, 2.5% of workers' SSNIT pension fund deducted at source, registration fees, and annual premiums. Other sources are returns on investments and support from international donors.

Due to enforcement issues, sing-up is voluntary, with about 40 percent of the population enrolled (World Bank, 2017). To subscribe, individuals are required to visit a registration center in their district and pay the annual premium. A NHIS card is then issued for use at a healthcare facility. To avoid moral hazard, members can only start enjoying benefits under the scheme one month after registration. All subscribers, including members exempt from paying premiums, are still required to pay a registration fee for access to the card. The card is valid for 5 years but subject to yearly renewals by payment of premiums unless exempt.

2.3 Empirical Strategy

We begin our analysis by separately estimating the effects of free schooling and insurance on fertility, and then estimate the effect of both reforms on fertility. Prior to the FPE, each district had a different school dropout rate, and these dropout rates also differed by cohort (cohort is determined by birthyear). District and cohort pre-policy dropout rates are used to compute the FPE intensity measure. We exploit the pre-policy district and cohort-specific dropout rates to identify the effect of FPE. We calculate intensity as the number of students who could be induced to stay in and complete primary school, relative to the number of students completing primary school prior to the reform. This strategy is used in Afrakomah (2021).[8] To determine a woman's intensity, we use birthyear to estimate expected graduation cohort.[9] Thus, women born in 1990 or prior, would have completed primary school in or before 2005, and would not have had access to any free schooling under the policy. The intensity measure

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[8] The computation of FPE intensities borrows from Afrakomah (2021).

[9] If a woman starts school on time at age 6 and has timely progression through the 9 years of primary school, then she should be 15 at the time of graduation, so women who were below 15 in 2005 are exposed to the FPE.

differs both by district and birth cohort. To identify the effect of FPE on fertility, we use the difference-in-differences specification:

$$y_{ijt} = \alpha + \beta FPE_{jt} + X'_{ijt}\Gamma + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + \varepsilon_{ijt} \quad (2.1)$$

where y_{ijt} is the fertility outcome for woman i in district j who was born in year t (i.e. number of births by age, dummies for first birth, first marriage, and first intercourse by age); FPE_{jt} is the FPE intensity measure for district j for cohort born in year t; Vector X'_{ijt} contains additional control variables including concurrent programs; δ_z is a set of survey year dummy variables because we use multiple waves of DHS; δ_j is the district-specific fixed effects that capture any time-invariant characteristics of the different districts; δ_t is the birthyear fixed effects that capture any cohort-specific differences; $\delta_j \times trend_t$ are district-specific linear trends that capture the linear trends within each district; and ε_{ijt} is the error term. β measures the effect of FPE. Standard errors are clustered at the district level to allow for within-district correlation.

We then estimate the effect of NHIS on fertility. The effect of NHIS on fertility can be estimated using ordinary least squares (OLS), which uses the actual insurance status in the data. However, if insurance take-up is correlated with unobservable characteristics that also affect fertility, the OLS estimates will be biased. For OLS results on the effect of NHIS on fertility, we estimate the equation given by

$$y_{ijt} = \alpha_0 + \alpha_1 NHIS_{ijt} + X'_{ijt}\Gamma + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + \varepsilon_{ijt} \quad (2.2)$$

where y_{ijt} is the fertility outcome for woman i in district j who was born in year t (i.e. number of births by age, dummies for first birth and first intercourse by age); $NHIS_{ijt}$ is a dummy for whether woman i in district j born in year t has insurance; Vector X'_{ijt} contains additional control variables including concurrent programs; δ_z is a set of survey year dummy variables because we use multiple waves of DHS; δ_j is the district-specific fixed effects that capture any time-invariant characteristics of the different districts; δ_t is the birthyear fixed effects that capture any cohort-specific differences; $\delta_j \times trend_t$ are district-specific linear trends that capture the linear trends within each district; and ε_{ijt} is the error term. α_1 measures the effect of NHIS. Standard errors are clustered at the district level to allow for within-district correlation.

To address any endogeneity concerns between insurance and fertility, we use distance to the closest registration center, following the reform, to predict the probability of insurance. To sign up for insurance, individuals are required to visit the NHIS registration center in their district. After the reform, women living closer to a registration center are more likely to be induced to take up insurance because of the lower traveling cost to a center. Distance, therefore, can be used to predict the probability an individual takes up insurance after the NHIS is introduced.[10] The first stage equation, in which insurance is predicted, is given by

$$NHIS_{ijt} = \gamma_0 + \gamma_1 distance_{ij}\, x\, post_t + \gamma_2\, distance_{ij} + X'_{ijt} + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + \varepsilon_{ijt} \qquad (2.3)$$

[10] This strategy borrows from Amoah (2021).

where $NHIS_{ijt}$ is instrumented by $distance_{ij}\ x\ post_t$; $post_t$ is a dummy variable equal to 1 if a woman is born in or after 1987; $distance_{ij}$ is woman i's distance to the NHIS registration center in district j[11]. The first stage estimate of γ_1 can be interpreted as the effect of NHIS on the probability of insurance take-up. All other variables are defined as in equation 2.2. The second stage equation can be defined as

$$y_{ijt} = \theta_0 + \theta_1 \widehat{NHIS_{ijt}} + \theta_2\, distance_{ij} + X'_{ijt} + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + \varepsilon_{ijt} \qquad (2.4)$$

where y_{ijt} is the fertility outcome for woman i in district j born in year t; $\widehat{NHIS_{ijt}}$ is the predicted probability of insurance from the first stage. The second stage uses the same set of controls as the first stage. θ_1 captures the causal effect of NHIS on fertility, exogenously generated by distance to the closest NHIS registration center. Standard errors are clustered at the district level to allow for within-district correlation.

Finally, we estimate the effect of FPE and NHIS on fertility. To do this, two conditions are required to identify whether the education and health reforms influence women's fertility. First, the same cohort of women affected by the FPE must be subsequently exposed to the NHIS in their reproductive ages, following the implementation of both reforms. Second, we exploit plausible exogenous variation in FPE and NHIS to address the potential endogeneity that arises from the fact that

[11] For a woman to be exposed to NHIS, she must be young enough at the start of the reform in 2005 so that she would make fertility decisions after NHIS is introduced. Fertility decisions usually begin at 18.Women aged 18 or below in 2005 are yet to make or just about to start making fertility decisions. We therefore consider these women (born in 1987 or after) to be exposed to NHIS.

insurance take-up can be correlated with unobservable characteristics that also affect women's fertility. To address these concerns, this study estimates an instrumented difference-in-difference-in-differences (DDD) model with district fixed effects that relies on the pre-existing district-level variation in school dropout rates combined with variation in the probability of insurance. Insurance probability is instrumented by distance to a NHIS registration center.

The effect of FPE and NHIS on fertility can be estimated by OLS using equation 2.5, which uses the reported insurance status in the data. As discussed above, the OLS estimates will be biased. For OLS results on the effect of FPE and NHIS on fertility, we estimate the equation given by

$$y_{ijt} = \mu_0 + \mu_1(FPE_{jt} x NHIS_{ijt}) + \mu_2 FPE_{jt} + \mu_3 NHIS_{ijt} + X'_{ijt}\Gamma + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + \varepsilon_{ijt} \quad (2.5)$$

where y_{ijt} is the fertility outcome for woman i in district j born in year t; all other variables are explained as above. Standard errors are clustered at the district level to allow for within-district correlation. μ_1 captures the OLS estimate of women exposed to FPE and have health insurance.

To address any endogeneity concerns, and as discussed above, we use distance to the closest registration center and FPE intensity, following the reforms, to predict a woman's probability of insurance when exposed to FPE. The first stage equations are given by

$$FPE_{jt}\ x\ NHIS_{ijt} = \beta_0 + \beta_1(FPE_{jt}\ x\ distance_{ij}\ x\ post_t) + \beta_2\ distance_{ij} + \beta_3\ FPE_{jt} + \beta_4\ (FPE_{jt}\ x\ distance_{ij}) + X'_{ijt}\Gamma + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + \varepsilon_{ijt} \quad (2.6)$$

$$NHIS_{ijt} = \gamma_0 + \gamma_1(distance_{ij}\ x\ post_t) + \gamma_2\ distance_{ij} + \gamma_3\ FPE_{jt} + X'_{ijt}\Gamma + \delta_z + \delta_j + \delta_t + \delta_j \times trend_t + v_{ijt} \quad (2.7)$$

where $FPE_{jg}\ x\ NHIS_{ijt}$ and $NHIS_{ijt}$ are instrumented by $FPE_{jg}\ x\ distance_{ij}\ x\ post_t$ and $distance_{ij}\ x\ post_t$, respectively; and $post_t$ is a dummy variable equal to 1 for women born after 1990. All other variables are defined as in equation 2.1.

The second stage equation can be defined as

$$y_{ijt} = \pi_0 + \pi_1(FPE_{jt}\ \widehat{x\ NHIS_{\iota jt}}) + \pi_2\ FPE_{jt} + \pi_3\widehat{NHIS_{\iota jt}} + \pi_4 distance_{ij} + \pi_5\ (FPE_{jt}\ x\ distance_{ij}) + X'_{ijt}\Gamma + \delta_z + \delta_j + \delta_t + \delta_j\ x\ trend_t + v_{ijt} \quad (2.8)$$

where y_{ijt} is the fertility outcome for woman i in district j born in year t; $FPE_{jt}\ \widehat{x\ NHIS_{\iota jt}}$ and $\widehat{NHIS_{\iota jt}}$ are the predicted exposure to both reforms and probability of insurance, respectively. The second stage uses the same set of controls as the first stage and standard errors are clustered at the district level to allow for within-district correlation.

2.4 Data

We use data from the 2003, 2008, 2014, 2016, and 2019 Ghana Demographic and Health Surveys (GDHS), National Health Insurance Authority (NHIA), and Integrated Public Use Microdata Series (IPUMS) International. A nationally representative sample of women aged 15-49 is surveyed in each cross section of the GDHS. Data collected include detailed information on education, health, contraceptive use, age at first birth, and the number of children.

We compute a different FPE intensity (FPE_{jt}) for each district and birth cohort from district completion rates for each grade prior to the policy using the IPUMS data. Our intensity measure captures the percentage increase in the number of primary school graduates if FPE would eliminate all future primary school attrition for the relevant test-taking cohort. For birth years before 1991, we set the level of intensity to 0 in all districts since the policy had not yet been implemented for these cohorts. For students who were expected to graduate in 2006, those who may have dropped out of school during the transition from grades 8 to 9, due to school fees, could now be persuaded by FPE to stay in school and complete grade 9. Thus, in the first year of FPE, we compute the intensity in each district as the number of students who finished grade 8 but dropped out between grades 8 and 9 pre-FPE, divided by the ninth-grade cohort. Thus, for students who were expected to graduate in 2007, the FPE intensity measure for that cohort is calculated as the number of individuals who finished grade 7, but did not finish grade 9, divided by the number who were in grade 9. The procedure for the calculation of intensity is extensively discussed in Afrakomah (2021).

We also compute distance to a NHIS registration center using data from the NHIA, which contains information on the location of the district registration offices, and the GDHS, which provides location information for surveyed women.

2.4.1 Summary statistics

Table 2.1 presents summary statistics for the full sample as well as for women who were not exposed to both reforms (women born in or before 1990) and women who were exposed to both reforms (women born after 1990)[12]. Our sample includes only

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[12] As explained above, women born after 1987 and 1990 are exposed to NHIS and FPE, respectively.

women aged 25 and above. Women in the pre-reforms sample have 0.03, 0.36 and 0.32 more births by ages 15, 20 and 25, respectively. While 4 percent of women in the control group had their first child by age 15, only 1 percent of women in the treated group had their first child by age 15. Additionally, 35 percent of women in the pre-reforms sample had their first child by age 20, compared to 7 percent of women in the post-reforms sample. These numbers increase to 60 percent and 56 percent by age 25 in the pre-reforms and post-reforms samples, respectively. The table shows similar patterns for age at first marriage and age at first intercourse.

Therefore, women born after 1990 are exposed to FPE and subsequently to NHIS during their reproductive ages.

Table 2.1: Summary statistics

	All	Born in or before 1990	Born after 1990
Number of births by age 15	0.03 (0.19)	0.04 (0.20)	0.01 (0.08)
Number of births by age 20	0.39 (0.68)	0.41 (0.70)	0.04 (0.21)
Number of births by age 25	1.08 (1.21)	1.09 (1.22)	0.77 (0.77)
First birth by age 15	0.03 (0.18)	0.04 (0.19)	0.01 (0.09)
First birth by age 20	0.34 (0.47)	0.35 (0.48)	0.07 (0.26)
First birth by age 25	0.58 (0.50)	0.60 (0.49)	0.56 (0.50)
First marriage by age 15	0.07 (0.27)	0.09 (0.29)	0.08 (0.27)
First marriage by age 20	0.56 (0.50)	0.71 (0.45)	0.56 (0.50)
First marriage by age 25	0.81 (0.40)	0.89 (0.31)	0.81 (0.40)
First intercourse by age 15	0.08 (0.27)	0.08 (0.28)	0.02 (0.13)
First intercourse by age 20	0.47 (0.50)	0.50 (0.50)	0.10 (0.30)
First intercourse by age 25	0.57 (0.50)	0.59 (0.49)	0.11 (0.32)

Note: Standard deviations are in parenthesis. Analysis is based on data for women in the 2003, 2008, 2014, 2016, and 2019 Ghana DHS. Standard deviations are in parenthesis.

2.5 Results

2.5.1 Effect of FPE on Fertility

We examine the effect of FPE on fertility by estimating equation 2.1 and report our findings in table 2.2. We find that in a district with intensity value of 1, FPE decreased the number of births by 0.01, 0.08, and 0.39 by ages 15, 20, and 25, respectively as shown in panel A. The decrease in the number of births by age 25 is significant at 1 percent. Additionally, we estimate the effect of FPE on the probabilities of first birth, first intercourse, and first marriage by specific ages and report the results in panels B, C, and D of table 2.2. Panel B shows that FPE decreases the probability of a woman having her first birth by ages 15 and 25. For a district with intensity value of 1, FPE led to 4 and 27 percentage points decline in the probability of first birth by these ages, respectively. The estimates are significant at 10 percent, at least. In panel C, we also find that free schooling decreases the likelihood of first intercourse by age 15 but increases its likelihood by ages 20 and 25. Finally, FPE decreases the probability of first marriage through age 25 as reported in panel D. The estimates in panels C and D are statistically insignificant.

The estimates for the effect of free schooling on first birth and first marriage provide evidence that women are postponing first birth and first marriage through age 25. Panel C shows that women are less likely to have first intercourse in their teens, which also suggests that free schooling delays sexual activity until their 20s. The results suggest that free schooling led to delayed first birth, sexual activity, and marriage for women in their younger ages.

Table 2.2: Effect of FPE on fertility by age

	15 (1)	20 (2)	25 (3)
Panel A: Number of births			
FPE	-0.01	-0.08	-0.39***
	(0.03)	(0.23)	(0.14)
N	19,370	19,370	19,370
R-squared	0.02	0.09	0.13
Panel B: First birth			
FPE	-0.04*	-0.22	-0.27***
	(0.02)	(0.14)	(0.08)
N	19,370	19,370	19,370
R-squared	0.02	0.12	0.11
Panel C: First intercourse			
FPE	-0.16	0.17	0.19
	(0.13)	(0.15)	(0.13)
N	12,660	12,660	12,660
R-squared	0.03	0.04	0.02
Panel D: First marriage			
FPE	-0.01	-0.06	-0.08
	(0.13)	(0.26)	(0.12)
N	12,660	12,660	12,660
R-squared	0.02	0.04	0.06

Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district and year dummy variables and NHIS control. The dependent variables in panels B, C, and D are binary, an indicator that equals 1 if true. Analysis in Panels C and D includes only data from 2003, 2008, and 2014 GDHS.
**** p<0.01, ** p<0.05, * p<0.1*

2.5.2 Effect of NHIS on fertility by age

To continue our analysis, we measure the effect of health insurance on fertility by estimating equation 2.2 and present the baseline OLS results in table 2.3. Insurance could increase fertility if it decreases the cost of having a child, or decrease fertility if women believe that children will grow old enough to take care of them in their old age (quality-quantity tradeoff). The results in panel A suggest a negative correlation between insurance and the number of births. Insurance decreases the number of births by 0.004, 0.08, and 0.15 births by ages 15, 20, and 25, respectively. A similar relationship between insurance and fertility is observed in panels B and C. Insurance decreases the probability of first birth by 1, 3, and 4 percentage points by ages 15, 20, and 25, respectively and decreases the probability of first marriage by 3 percentage points each by ages 15 and 20. Most of the estimates in table 2.3 are statistically significant at 1 percent. These results suggest that insurance is associated with decreased fertility in women by reducing the number of births and delaying first birth and first intercourse.

Table 2.3: OLS Results of effect of NHIS on fertility by age

	15 (1)	20 (2)	25 (3)
Panel A: Number of births			
Insured	-0.004	-0.08***	-0.15***
	(0.003)	(0.01)	(0.03)
N	19,370	19,370	19,370
R-squared	0.02	0.09	0.13
Panel B: First birth			
Insured	-0.01***	-0.03***	-0.04***
	(0.00)	(0.01)	(0.01)
N	19,370	19,370	19,370
R-squared	0.02	0.11	0.11
Panel C: First intercourse			
Insured	-0.03***	-0.03***	0.01
	(0.01)	(0.01)	(0.01)
N	12,660	12,660	12,660
R-squared	0.03	0.04	0.02

Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district and year dummy variables and NHIS control. The dependent variables in panels B and C are binary, an indicator that equals 1 if true. Analysis in Panels C includes only data from 2003, 2008, and 2014 GDHS.
**** p<0.01, ** p<0.05, * p<0.1*

These OLS estimates, however, only show correlations, as discussed earlier. To estimate the causal impact of insurance on fertility, we use a 2SLS estimation strategy based on the NHIS in Ghana and estimate equations 2.3 and 2.4. The first stage results from these estimations are presented in table 2.4. Column 1 presents the results for all women aged 25 and above in our dataset, whiles column 2 includes women aged 25 and above in the 2003, 2008, and 2014 DHS.[13] Our results suggest that, following the reform, insurance take-up decreases by 0.4 percentage point (using all women aged 25 and above) and 0.5 percentage point (using subsample) if distance to a registration center increases by 1 kilometer.

Table 2.4: First stage results

	Insured (Full sample) (1)	Insured (Subsample) (2)
Distance x post	-0.004***	-0.005***
	(0.001)	(0.002)
Distance	-0.007**	-0.008***
	(0.001)	(0.001)
Post	0.05	0.04
	(0.12)	(0.11)
F-stat	14.73	7.85
N	19,370	12,660

Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district, and year dummy variables and FPE control. Analysis in column (2) includes only data from 2003, 2008, and 2014 GDHS.
**** p<0.01, ** p<0.05, * p<0.1*

The 2SLS estimates for the effects of insurance on fertility are presented in table 2.5. In contrast to the OLS results, the 2SLS estimates show that insurance increases

[13] Only 2003, 2008, and 2014 GDHS contain information on age at first intercourse.

total children born by 0.32, 0.56, and 0.94 births by ages 15, 20, and 25, respectively, as reported in panel A. Unsurprisingly, insurance reduces the timings of first birth and first intercourse. In panel B, insurance increases the likelihood of having first birth by 12, 15, and 35 percentage points by ages 15, 20, and 25, respectively. Although insignificant, insurance also increases the probability of first sexual activity by 24, 46, and 58 percentage points by ages 15, 20, and 25, respectively. Even though most of the estimates are insignificant, the estimates suggest insurance increases fertility, and provide evidence of the importance of the cost of childbearing in fertility decisions.

Table 2.5: 2SLS effect of NHIS on fertility by age

	15 (1)	20 (2)	25 (3)
Panel A: Number of births			
Insured	0.32* (0.17)	0.56 (0.50)	0.94 (1.13)
N	19,370	19,370	19,370
Panel B: First birth			
Insured	0.12 (0.34)	0.15 (0.15)	0.35* (0.21)
N	19,370	19,370	19,370
Panel C: First intercourse			
Insured	0.24 (0.75)	0.46 (0.64)	0.58 (1.74)
N	12,660	12,660	12,660

Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district and year dummy variables and FPE control. The dependent variables in panels B and C are binary, an indicator that equals 1 if true. Analysis in Panels C includes only data from 2003, 2008, and 2014 GDHS.
**** p<0.01, ** p<0.05, * p<0.1*

2.5.3 Effect of FPE and NHIS on fertility

Finally, we estimate the effect of FPE and NHIS on fertility. We measure the OLS relationship between the reforms and fertility by estimating equation 2.5 and report the results in columns 1, 3, and 5 of table 2.7. We estimate the equation using the reported insurance status from the data, not the predicted probability of insurance from the first stage. In panel A, OLS estimates show that women who live in a district with FPE intensity value of 1 and have health insurance have 0.02, 0.19, and 0.29 more births by ages 15, 20, and 25, respectively. The estimates for ages 20 and 25 are significant at 10 percent, at least. We observe a similar relationship between the reforms and the timing of first birth. In panel B, we find that exposure to both FPE and NHIS increase the probability of first birth by 3, 5, and 6 percentage points by ages 15, 20, and 25, respectively. The estimate for age 15 is statistically significant at 1 percent. We also find that, although insignificant, FPE and NHIS increase the likelihood of first sexual activity by 9, 16, and 18 percentage points by ages 15, 20, and 25, respectively, as reported in panel C. In effect, the OLS estimates show that fertility increases for women who have insurance and are exposed to free schooling.

These estimates, however, are unlikely to describe a causal relationship between the reforms and fertility. An exogenous increase in exposure to FPE and NHIS generated by the intensity of FPE and distance to an NHIS registration center, following the reform, is used to address this concern. We estimate the first stage equations, equations 2.6 and 2.7 and report the results in table 2.6. The estimates show that, using the full sample, a reduction in distance to a registration center by 1 kilometer increases the probability of insurance take-up by 1.9 percentage point, and by an additional 0.7 percentage points if you are also exposed to FPE, as reported in columns 1 and 2 of table 2.6, respectively. The results are consistent for the subsample, which includes only information from 2003, 2008, and 2014 GDHS. The estimates from the first stage show the FPE intensity and distance measures' combined ability to identify the probability of insurance when exposed to both policies.

Table 2.6: First stage results – effect of FPE and NHIS on fertility

	FPE x NHIS (Full sample) (1)	NHIS (Full sample) (2)	FPE x NHIS (Subsample) (3)	NHIS (Subsample) (4)
FPE x Distance x post	-0.007***		-0.004***	
	(0.001)		(0.002)	
Distance x post		-0.019***		-0.004***
		(0.001)		(0.001)
Post	0.005	0.13		
	(0.01)	(0.09)		
F-stat	16.13	11.85	16.97	7.63
N	19,370	19,370	12,660	12,660

Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district, and year dummy variables. Analysis in columns (3) and (4) include only data from 2003, 2008, and 2014 GDHS.
**** p<0.01, ** p<0.05, * p<0.1*

The second stage of the 2SLS model estimates the relationship between the predicted level of exposure to FPE and NHIS and fertility, as described by equation 2.8, and reports the results in table 2.7. The effect of FPE on fertility depends on a woman's probability of being insured, and vice versa. In panel A, we estimate the effect of the reforms on the number of births. The coefficient of FPE in columns 2, 4, and 6 is negative while the coefficients of NHIS and the interaction term are positive. The positive interaction coefficient implies that the higher the probability of insurance, the less negative the effect of FPE, and the higher the FPE intensity, the more positive the coefficient of NHIS. Specifically, for a woman with probability of insurance α percent, FPE will change her number of births by ($-0.29 + 0.34*\alpha$), ($-0.72 + 0.68*\alpha$), and ($-0.95 + 0.96*\alpha$) births by ages 15, 20, and 25, respectively. For instance, if a woman has a 10 percent probability of having insurance, FPE reduces her number of births by 0.26 (= -

0.29 + 0.34*0.10), 0.65 (= -0.72 + 0.68*0.10), and 0.85 (= -0.95 + 0.96*0.10) by ages 15, 20, and 25, respectively. On the other hand, FPE reduces her number of births by 0.12, 0.38, and 0.47 births by ages 15, 20, and 25, respectively, if she has a 50 percent probability of being insured. The effects of FPE on fertility become less negative as her probability of insurance increases.

Alternatively, if a woman lives in a district with FPE intensity value β, NHIS increases number of births by ($0.08 + 0.34*\beta$), ($0.83 + 0.68*\beta$), and ($2.84 + 0.96*\beta$) by ages 15, 20, and 25, respectively. For example, for a woman who lives in a district with FPE intensity value 0.5, NHIS increases her number of births by 0.25, 1.17, and 3.32 births by ages 15, 20, and 25, respectively. However, NHIS increases her number of births by 0.42, 1.51, and 3.82 births by the respective ages if FPE intensity value is 1. This suggests the effects of insurance on fertility become more positive as a woman's exposure to FPE increases. The coefficients of the interaction term are, however, not statistically significant at the 10 percent level.

In panels B and C of table 2.7, we estimate the effect of FPE and NHIS on the timings of first birth and first sexual intercourse by ages. The coefficients of the interaction term remain positive across all ages for both outcomes. Similar to the results in panel A, the positive interaction coefficient implies that the higher the probability of insurance, the less negative the effect of FPE, and the higher the FPE intensity, the more positive the effect of NHIS. In panel B, given probability of insurance, α percent, FPE reduces the probability of having first birth by ($-0.17 + 0.14*\alpha$), ($-0.38 + 0.18*\alpha$), and ($-0.74 + 0.48*\alpha$) percentage points by ages 15, 20, and 25, respectively. Alternatively, with intensity value β, NHIS increases the likelihood of having first birth by ($0.01 + 0.14*\beta$), ($0.35 + 0.18*\beta$), and ($0.64 + 0.48*\beta$) percentage points by ages 15, 20, and 25, respectively. In panel C, we observe a similar relationship. FPE reduces the probability of having first birth by (-0.05 + 0.43*α), (-0.20 + 0.53*α), and (-0.98 + 0.60*α) percentage points by ages 15, 20, and 25, respectively. And NHIS increases the likelihood of having first intercourse by (0.13 + 0.43*β), (0.23 + 0.53*β), and (0.66 + 0.60*β) percentage points by ages 15, 20, and 25, respectively. The coefficients of the interaction term and the main effects in panels B and C are, however, not statistically significant at all conventional levels.

Table 2.7: Effect of FPE and NHIS on fertility by age

	15 OLS (1)	15 2SLS (2)	20 OLS (3)	20 2SLS (4)	25 OLS (5)	25 2SLS (6)
Panel A: Number of births						
FPE x NHIS	0.02		0.19***		0.29*	
	(0.02)		(0.07)		(0.17)	
$\widehat{FPE\ x\ NHIS}$		0.34		0.68		0.96
		(0.36)		(1.90)		(1.94)
FPE		-0.29		-0.72		-0.95
		(0.30)		(4.51)		(1.70)
$\widehat{NHIS}$		0.08		0.83		2.84**
		(0.08)		(1.34)		(1.244)
Number of clusters	110	110	110	110	110	110
N	19,370	19,370	19,370	19,370	19,370	19,370
Panel B: First birth						
FPE x NHIS	0.03***		0.05		0.06	
	(0.01)		(0.05)		(0.19)	
$\widehat{FPE\ x\ NHIS}$		0.14		0.18		0.48
		(1.33)		(0.20)		(1.78)
FPE		-0.17		-0.38		-0.74
		(0.16)		(1.33)		(2.74)
$\widehat{NHIS}$		0.01		0.35		0.64
		(0.10)		(1.78)		(0.78)
Number of clusters	110	110	110	110	110	110
N	19,370	19,370	19,370	19,370	19,370	19,370
Panel C: First intercourse						
FPE x NHIS	0.09		0.16		0.18	
	(0.13)		(0.18)		(0.45)	
$\widehat{FPE\ x\ NHIS}$		0.43		0.53		0.60
		(0.50)		(0.54)		(2.25)
FPE		-0.05		-0.20		-0.98
		(0.11)		(1.48)		(1.33)
$\widehat{NHIS}$		0.13		0.23		0.66
		(1.25)		(1.08)		(0.44)
Number of clusters	110	110	110	110	110	110
N	19,370	19,370	19,370	19,370	19,370	19,370

*Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district and year dummy variables. The dependent variables in panels B and C are binary, an indicator that equals 1 if true. Analysis in Panels C includes only data from 2003, 2008, and 2014 GDHS. *** p<0.01, ** p<0.05, * p<0.1*

We estimate alternative versions of the triple DDD model with FPE or distance dummies. We estimate the triple DDD model and replace FPE intensity values with an FPE dummy (and keep NHIS distance continuous) for whether the district had an intensity value greater than the mean intensity. The results are reported in table 2.8. We also estimate the triple DDD model and replace distance with a distance dummy (and keep FPE intensity continuous) for whether a woman's distance to a registration center is less than the mean distance. The results are presented in table 2.9. Finally, we estimate the triple DDD model where we replace FPE intensity values with the FPE dummy and replace distance with the distance dummy. We report the results in table 2.10.

In table 2.8, the coefficients of the interaction term are positive in all estimations. The results in panel A show that for a woman living in a low FPE intensity district (intensity less than the mean intensity), NHIS increases her number of births by 0.34, 0.42, and 1.84 by ages 15, 20, and 25, respectively. But for a woman living in a high FPE intensity district (intensity greater than the mean intensity), NHIS increases her number of births by 0.45 (0.11 + 0.34), 0.58 (0.16 + 0.42), and 2.74 (0.90 + 1.84) births by ages 15, 20, and 25, respectively. These suggest that high exposure to FPE increases the effect of NHIS on the number of births. Similarly, from panels B and C, free schooling increases the effect of NHIS on the timings of first birth and first sexual intercourse. The coefficients are statistically insignificant at all levels.

Table 2.8: Model with FPE dummy – effect of FPE and NHIS on fertility by age

	15 2SLS (1)	20 2SLS (2)	25 2SLS (3)
Panel A: Number of births			
$\widehat{FPE\ x\ NHIS}$	0.11	0.16	0.90***
	(1.05)	(0.14)	(0.32)
FPE	-0.03	-0.11	-0.61***
	(0.61)	(0.09)	(0.19)
$\widehat{NHIS}$	0.34	0.42	1.84
	(0.81)	(0.28)	(1.64)
Number of clusters	110	110	110
N	19,370	19,370	19,370
Panel B: First birth			
$\widehat{FPE\ x\ NHIS}$	0.07	0.26	0.90
	(0.11)	(0.29)	(0.92)
FPE	-0.05	-0.17	-0.87
	(0.07)	(0.17)	(0.56)
$\widehat{NHIS}$	0.18	0.41	0.89
	(0.23)	(0.62)	(0.78)
Number of clusters	110	110	110
N	19,370	19,370	19,370
Panel C: First intercourse			
$\widehat{FPE\ x\ NHIS}$	0.16	0.17	0.42
	(0.14)	(0.42)	(0.57)
FPE	-0.07	-0.10	-0.32
	(0.24)	(0.09)	(0.33)
$\widehat{NHIS}$	0.14	0.73	0.90
	(0.36)	(0.58)	(0.86)
Number of clusters	110	110	110
N	19,370	19,370	19,370

Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district and year dummy variables. The dependent variables in panels B and C are binary, an indicator that equals 1 if true. Analysis in Panels C includes only data from 2003, 2008, and 2014 GDHS.
**** p<0.01, ** p<0.05, * p<0.1*

In table 2.9, we report the results of another alternate model, where we replace distance with a distance dummy. In panel A, the results show that for a woman who has low probability of insurance (because distance to center is greater than mean distance), FPE decreases the number of births by 0.14, 0.61, 1.00 births by ages 15, 20, and 25, respectively. However, if a woman has high probability of insurance (distance to center less than mean distance), FPE increases number of births by 0.07 (0.21 – 0.14) births by age 15 and decreases number of births by 0.27 (0.34 – 0.61) and 0.58 (0.42 – 1.00) by ages 20 and 25, respectively. We observe a similar relationship between fertility and fertility in panels B and C. These suggest that high probability of being insured lessens the negative effect (less negative) of FPE on fertility. All coefficients are not statistically significant.

Table 2.9: Model with Distance dummy – effect of FPE and NHIS on fertility by age

	15 2SLS (1)	20 2SLS (2)	25 2SLS (3)
Panel A: Number of births			
$\widehat{FPE\ x\ NHIS}$	0.21	0.34	0.42
	(0.66)	(0.55)	(1.28)
FPE	-0.14	-0.61	-1.00
	(0.52)	(1.00)	(1.72)
$\widehat{NHIS}$	0.41	0.45	0.59
	(0.99)	(0.48)	(1.05)
Number of clusters	110	110	110
N	19,370	19,370	19,370
Panel B: First birth			
$\widehat{FPE\ x\ NHIS}$	0.11	0.14	0.23
	(2.06)	(1.14)	(0.45)
FPE	-0.01	-0.14	-0.21
	(0.34)	(0.35)	(0.92)
$\widehat{NHIS}$	0.33	0.34	0.51
	(0.33)	(0.65)	(0.74)
Number of clusters	110	110	110
N	19,370	19,370	19,370
Panel C: First intercourse			
$\widehat{FPE\ x\ NHIS}$	0.11	0.51	0.76
	(0.79)	(1.60)	(1.37)
FPE	-0.35	-0.66	-0.90
	(1.29)	(1.12)	(0.65)
$\widehat{NHIS}$	0.45	0.51	0.55
	(0.65)	(0.34)	(0.80)
Number of clusters	110	110	110
N	19,370	19,370	19,370

Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district and year dummy variables. The dependent variables in panels B and C are binary, an indicator that equals 1 if true. Analysis in Panels C includes only data from 2003, 2008, and 2014 GDHS.
**** p<0.01, ** p<0.05, * p<0.1*

Finally, in table 2.10, we report the results of our last alternate model that includes only FPE and distance dummies. The coefficient of the interaction term measures additional changes in fertility outcomes among women who lived in a high FPE intensity district and were more likely to have insurance (because they lived closer to a registration center). In panel A, we find that women who were highly exposed to both reforms have 0.03, 0.59, and 0.80 more births by ages 15, 20, and 25, respectively. In panels B and C, high exposure to both reforms additionally increases the probabilities of first birth and first intercourse by all ages.

Table 2.10: FPE and Distance dummies – effect of FPE and NHIS on fertility

	15 2SLS (1)	20 2SLS (2)	25 2SLS (3)
Panel A: Number of births			
$\widehat{FPE\ x\ NHIS}$	0.03	0.59	0.80
	(0.30)	(1.09)	(0.74)
FPE	-0.35	-0.59	-0.96
	(0.66)	(1.39)	(0.90)
$\widehat{NHIS}$	0.46	0.68	0.82
	(0.77)	(0.64)	(1.31)
Number of clusters	110	110	110
N	19,370	19,370	19,370
Panel B: First birth			
$\widehat{FPE\ x\ NHIS}$	0.19	0.40	0.42
	(0.37)	(1.07)	(0.67)
FPE	-0.26	-0.30	-0.61
	(0.40)	(0.65)	(2.66)
$\widehat{NHIS}$	0.29	0.57	0.62
	(0.16)	(0.80)	(1.25)
Number of clusters	110	110	110
N	19,370	19,370	19,370
Panel C: First intercourse			
$\widehat{FPE\ x\ NHIS}$	0.12	0.13	0.84
	(1.00)	(0.66)	(1.96)
FPE	-0.06	-0.45	-0.70
	(1.00)	(1.19)	(0.62)
$\widehat{NHIS}$	0.26	0.29	0.31
	(2.00)	(0.37)	(1.22)
Number of clusters	110	110	110
N	19,370	19,370	19,370

Data are from 2003, 2008, 2014, 2016 and 2019 GDHS. Standard errors, clustered at the district level, are in parenthesis. All regressions include the district linear trends, district and year dummy variables. The dependent variables in panels B and C are binary, an indicator that equals 1 if true. Analysis in Panels C includes only data from 2003, 2008, and 2014 GDHS.
**** p<0.01, ** p<0.05, * p<0.1*

2.6 Conclusion

This paper finds evidence that free schooling led to a decrease in number of births, and that the reduction in fertility is generated through a delay in first birth and marriage. FPE significantly reduced number of births by 0.39 by age 25, which is similar in magnitude to what Keats (2018), Chicoine (2021), and Zenebe Gebre (2020) find in Uganda, Ethiopia, and Malawi, respectively. We also find that removal of healthcare user fees led to an increase in number of births, generated through early first birth. NHIS increased number of births by 0.94 by age 25, which provides evidence that the cost of childcare is an important factor in making fertility decisions.

Finally, we estimate the effect of FPE and NHIS on fertility. We find that higher exposure to NHIS reduces the negative effect of FPE on fertility, and a higher exposure to FPE increases the positive effect of NHIS on fertility. This is an important finding because most developing countries that have introduced free schooling also have health insurance programs like the NHIS. If these countries aim to reduce fertility, more needs to be done in terms of educating the people about the benefits of a reduction in fertility.

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