Financial protection and child health: A Propensity Score Matching analysis

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Contents

Abstract

One of the targets of Sustainable Development Goal (SDG) number 3 is to achieve universal coverage, including financial risk protection for all. Financial protection aims to promote and maintain individuals' health outcomes through securing access to treatment and care. The lack of health insurance and unaffordability of health care services increases the risk of poor health outcomes in children. This study uses data from the South African National Health and Nutrition Examination Survey (SANHANES-1), to investigate the relationship between child health outcomes measured by anaemia, cough, fever, diarrhoea, vitamin A deficiency, wasting and stunting, and financial protection. The study uses Propensity Score Matching (PSM) to determine the average treatment effects and treatment effects on the treated of financial protection. Four matching algorithms namely: nearest neighbour, calliper radius, kernel and local linear regressions were used to ascertain the robustness of the econometric results. The results indicate a statistically significant negative relationship between financial protection and coughing and fever when there is strong financial protection. The average treatment effects on the treated vary across the sex of the child. Strong financial protection reduces the prevalence of childhood illnesses more in females than it does in males. The study indicates that financial protection affects child health outcomes differently and therefore produces mixed results. These differences are attributable to the fact that the public sector provides free primary health care services for children in South Africa.

Keywords: child health, financial protection, Propensity Score Matching

1. Introduction

Sustainable development goal number three relates to ensuring healthy lives and promoting well-being for all and at all ages (United Nations, 2015). One of the targets within this goal is to achieve universal coverage, including financial risk protection for all (United Nations, 2015). There are also targets within this goal aimed at improving child health outcomes. Financial protection in health refers to the extent in which individuals are protected from financial consequences associated with illness (Moreno-Serra, Millett & Smith, 2011). In simple terms, financial protection relates to having means like health insurance that enables access to health care services. Health insurance is referred to as the main mechanism that decreases health expenditures resulting from disease (Chen & Chu, 2019). Its main function is to reduce the economical obstacles for health care treatments, contain financial risks and enable financial accessibility to health care services (Chen & Chu, 2019). However, there are other costs like co-payments and deductibles which may prove to be difficult for individuals with health insurance to pay and therefore, having health insurance does not necessarily protect individuals completely from the financial consequences associated with illness or diseases. As such, one should take a broader perspective on how financial protection is defined and look beyond access to health insurance as the only indicator of being financially protected. Moreover, it can be said that not everyone without health insurance is not financially protected.

The endmost aim of financial protection is to promote and maintain individuals' health outcomes through securing access to treatment and care. An imperative for children who are vulnerable because of chronic conditions or social circumstances is related to having financial protection (Szilagyi, Schuster & Cheng, 2009). The lack of health insurance and unaffordability of health care services increases the risk of poor health outcomes in children. This study investigates the relationship between financial protection and health outcomes in children. There is limited literature on financial protection and child health outcomes in South Africa and internationally. This study aims to contribute to the existent literature and inform policy makers on the potential child health benefits owed to financial protection. This study is unique because it uses three proxies for treatment. Moreover, to test if treatment affects child health outcomes differently or the same, seven health outcomes are employed in the analysis.

The second section of this paper expands on what literature says about financial protection and child health outcomes. Generally, there is a positive relationship between financial protection and child health outcomes. The Grossman's model paints a picture on the importance of children being financially protected from the early stage of their lives. The third section explains the methodology used in this paper. Propensity Score Matching was chosen to show that financial protection as treatment has the potential of improving child health outcomes. It is also commonly used with observational data and when randomised controlled trials studies cannot or have not been conducted. The fourth section reports the statistical analysis which includes descriptive statistics and results of the average treatment on the treated (i.e. ATT) and average treatment effects (i.e. ATE). The results are further elaborated on in the discussion, which is section 5, followed by the limitations of the paper in section 6.

2. Literature Review

2.1. Background

In the apartheid era, poor people, women, and children who were African were harshly affected by the rules and regulations of government (Chapra *et al*., 2009). This era was characterised by high child mortality rates. Women and children lived in a world of under-resourced health care services, lack of nutritious foods due to affordability and were exposed to environmental risks (Chapra *et al.,* 2009). Post 1994 elections, the new government prioritised child health by removing user-fees for services that affected mothers and children at the primary health care level (Chapra *et al.,* 2009). The vast majority of South Africans use the public sector as it provides free primary care and minimal charges for inpatient care (Govender, Ataguba & Alaba, 2014). The minimal charges or co-payments may be catastrophic and impoverishing to some households and therefore discourage them to seek and access health care services. There have been improvements in addressing child mortality for the period between 2000 and 2015 in South Africa, but the improvements are not significant as they occur at a slow pace and the performance still falls short of the SDG targets (Dorrington *et al.*, 2018).

The public sector is often overcrowded and provides poor quality of health care services due to the lack of adequate health professionals, which results in long queues and public facilities are often far from people (Govender *et al.,* 2014). Those that afford private health insurance, however, use the private sector which only covers approximately 20% of South Africans. There are often complications in home delivery processes and overcrowded hospitals, with shortages of health care workers, which result in child morbidities and a low stock of health for children (Govender *et al.,* 2014). These home deliveries are done most often because people cannot afford health care costs, or they must queue in public hospitals to get assisted even when the need for health care is urgent. Having a private health insurance reduces uncertainty and hedges against financial risks (Bhattacharya, Hyde & Tu, 2014). Financial protection will enable children to access any facility (i.e. private, or public).

Altogether, poor child health outcomes are partly attributable to the inherited health care systems of the apartheid era and the inequalities associated with this era. Although efforts have been made to improve child health outcomes over the years, health outcomes are still poor. It was established that most low-socio-economic households cannot afford health insurance let alone pay out-of-pocket to access health care services that will improve their children's health. Put simply, there are often hardships in generating financial resources to pay for a health insurance on a month-to-month basis in low-income households and getting services from the private sector because of high levels of unemployment and informal sector employment (Govender *et al.,* 2014). In the next section, the theory and literature that supports the proposition that financial protection has the potential to improve child health is reviewed.

2.2. Theory

Chen and Chu (2019) describe heath as the state of mental, physical, and social wellbeing. In the Grossman model, health is a stock that needs to be invested in, in order to increase it and it depreciates with age (Bhattacharya *et al.,* 2014). People are born with a certain level of health stock, therefore health investments in children and expectant mothers are more effective than in adults. This is because unless a child is born with chronic illnesses or defects, the level of health depreciation is lower in children than it is in adults (Chen & Chu, 2019). If there are no health investments in children at a young age, there is a possibility that the lack of investment in their health as children will have a significant impact on their health later in their lives. Children's health does not only affect their own personal wellbeing but can affect the society's health and has potential influence on the country's future (Chen & Chu, 2019). Ways of investing in health include seeking health care, accessing health care and receiving treatment (Bhattacharya *et al.,* 2014). There are financial means required for one to access health care services. Out-of-pocket payments and health insurance are the mechanisms that enable access to health care services which lead to better health outcomes for individuals. They also serve as some form of financial protection against diseases.

Govendor *et al.,* (2014) and Chen and Chu (2019) suggest that there is a connection between poor child health outcomes and lack of financial protection and on the other hand, good health in children is associated with having financial protection. It is also believed that through universal health insurance, uninsured children's health outcomes will improve. The latter point reflects an element of theory of change, and it is relevant to this study. Theory of change explains the pathways in which an intervention contributes to the final impact of the intervention (Rogers, 2014). The hypothesis of this study is that financial protection is expected to reduce child morbidity and mortality from diarrhoea, cough, fever, anaemia, stunting, wasting and to improve vitamin A deficiency (i.e. The definitions of key concepts is provided for in Box 1).

Given the problem of high morbidity and mortality due to anaemia, vitamin A deficiency, diarrhoea, fever, cough, stunting and wasting, it is believed that through financial protection, the prevalence of these child health outcomes will decrease. This involves enrolling all children in South Africa under a universal health insurance offering complete financial protection where there are zero co-payments and no minimal fees to allow for inclusivity. This makes access to health care easier and increases the utilisation of health care services. Gupta *et al.,* (2021) argue that children's development becomes poor when adequate responsive care is not received. The assumption is that by scrapping user fees and co-payments, health seeking behaviour for children's illnesses will increase. If there is no financial hardship and children are able to consult every time they get sick and get the right medication, the prevalence of child illnesses like diarrhoea will decline and reduce in its severity.

Financial protection through universal health insurance will also reduce out-of-pocket payments for households who are currently insured but cannot afford health care services due to co-payments, co-insurance and deductibles. The effect of low health stock mentioned in the Grossman's model, which leads to a reduction in labour productivity, will also decline if children's health is improved by being financially protected. This will likely result in an increase in productive life years.

Box 1: Definition of key concepts

Stunting refers to the impaired growth and development that children experience from poor nutrition, repeated infection, and inadequate psychosocial stimulation.

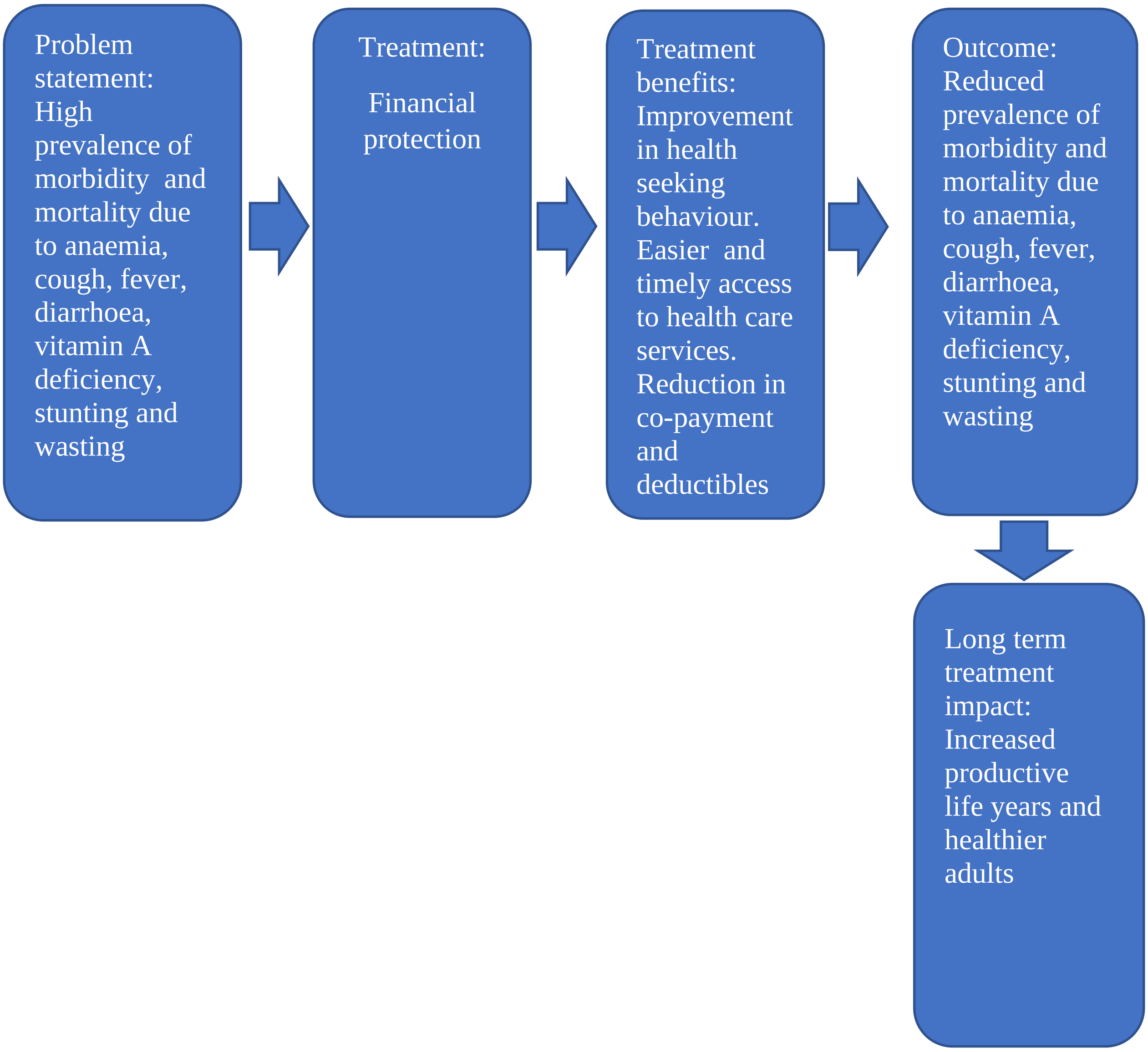
Wasting occurs when a child's weight is too low for their height. It is often referred to as acute malnutrition where a child has experienced short periods of undernutrition resulting in significant wastage of muscle and fat tissue.

Vitamin A deficiency is the lack of vitamin A in blood and tissues and can result from a dietary intake of vitamin A that is inadequate to satisfy physiological needs

Anaemia is a condition in which the number of red blood cells or the haemoglobin concentration within them is lower than normal.

Source: WHO (2015), Ritchie (2021) & WHO (2022)

Figure 1: Main pathways of treatment impact



2.3. Empirical Evidence

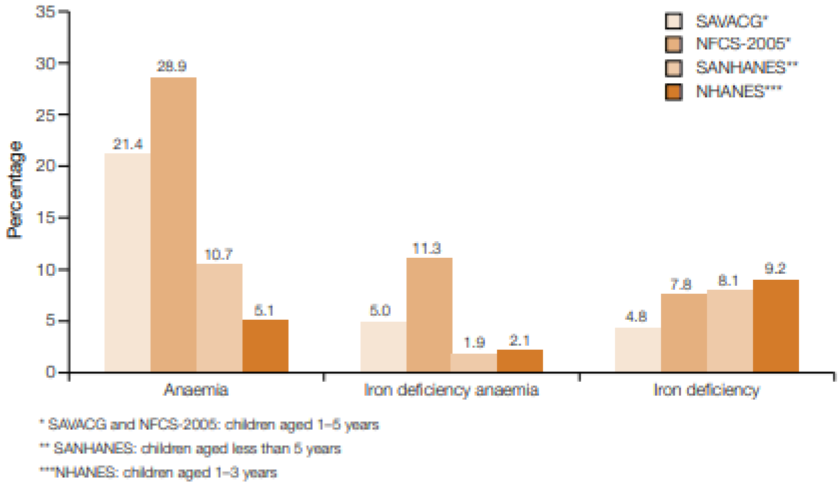
The trends in child health outcomes in South Africa are important to note. The 2013 SANHANES-1 reports on the prevalence of stunting, wasting and anaemia in South African children. Stunting and wasting are classified by gender (i.e. boys and girls). Table 1 reports that 26.9% of boys aged 1-3 years are stunted and 3.8% are wasted. Of these stunted boys, 23.2% are from rural informal regions, whilst 13.6% were from urban formal regions. Northwest and Mpumalanga have the highest percentage of stunting of 23.1% whilst Gauteng has the least percentage of stunting in boys. Furthermore, 1.5% of girls aged 1-3 years were wasted and 25.9% were stunted. Of these wasted girls, 3.4% came from rural informal regions and 0.6% were from urban informal regions. Northwest had the highest percentage of wasting at 5.2% whilst Gauteng had the least prevalence of 0.4%. These statistics indicate that both stunting and wasting are more prevalent in boys than in girls and that Northwest has the highest prevalence of both stunting and wasting while Gauteng has the least. The provincial and regional analysis of these child health indicators show that stunting and wasting are still a concern in South Africa. Policy makers ought to keep these trends in mind when formulating child health policies.

Table 1: Stunting and wasting for females and males under fifteen years

	Boys		Girls	
Background characteristics	Stunting (Below-2SD) %	Wasting (Below-2SD) %	Stunting (Below -2 SD) %	Wasting (Below-2SD) %
Age				
0-3 years	26.9	3.8	25.9	1.5
4-6 years	13.5	2.6	9.5	1.0
Locality				
Urban formal	13.6	4.3	10.4	1.8
Urban informal	17.0	1.0	20.9	0.6
Rural formal	18.4	2.9	13.9	1.5
Rural informal	23.2	9.3	17.0	3.4
Province				
Western Cape	17.5	2.0	13.9	1.3
Eastern Cape	21.6	1.6	15.6	3.2
Northern Cape	22.8	18.5	15.0	5.1
Free state	19.4	1.7	22.1	1.4
Kwa-Zulu_Natal	13.5	2.4	14.4	*
NorthWest	23.1	8.5	17.8	5.2
Gauteng	11.9	3.6	10.0	0.4
Mpumalanga	23.1	2.8	13.0	1.8
Limpopo	13.7	6.5	9.4	2.8

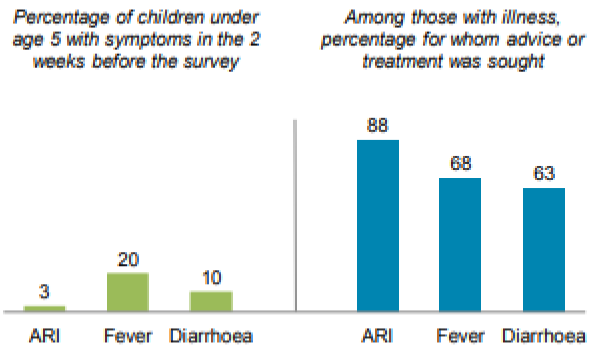
Source: (Shisana *et al.*, 2013 :207-208)

Figure 2: The prevalence of anaemia, iron deficiency anaemia in children under 5



Source: (Shisana *et al.*, 2013 :207-208)

Figure 3: Prevalence of treatment and childhood illness



Source: (National Department of Health, Statistics South Africa (Stats SA), South African Medical Research Council (SAMRC 2019: 158)

Figure 2 shows the percentage of anaemia, iron deficiency anaemia for four different studies namely: SANHANES-1, SAVACG, NFCS-2005 and NHANES. In the SANHANES-1 report, anaemia prevalence is at 10.7%, iron deficiency at 1.9% and iron deficiency anaemia at 8.1%. Figure 3 shows the prevalence of childhood illnesses for children under five years in South Africa and the percentage that sought treatment or advice for the illnesses. The identified childhood illnesses were Acute Respiratory Infection (ARI), fever and diarrhoea which reported the prevalence of 3%, 20% and 10% respectively at the time of the study (National Department of Health, Statistics South Africa (Stats SA), South African Medical Research Council (SAMRC 2019)). Of the ARI group, 88% sought treatment or advice, 68% of those with fever sought advice or treatment and 63% of those with diarrhoea sought treatment or advice. The trends show that not every child is able to get treatment or advice for illnesses.

Studies on the impact of financial protection on child health mainly employ access to health insurance as its measure of financial protection. These studies are briefly reviewed in this section. Chen and Chu (2019) studied the impact of health insurance coverage on child health outcomes in China. They used height-for-age (i.e. HAZ) to measure child health. Chen and Chu (2019) adopted the instrumental probit model and employed propensity score matching to investigate the causal impact of health insurance coverage on child health. They found that enrolling in a health insurance improved children's health outcome. Govendor *et al.,* (2014) studied private health insurance coverage within households in South Africa. They uncover the socio-economic problems that lead to not enrolling in a health insurance and they relate them to affordability. The authors state that when faced with affordability problems, children are often left off the health insurance. The reason for the exclusion is that household income hardly provides for the entire household to be insured and resources are therefore spread unevenly amongst the household in terms of health insurance coverage (Govendor *et al.,* 2014). The lack of financial protection for children may result in poorer health outcomes.

Haven *et al.,* (2018) conducted research on how a community-based health insurance in Uganda was able to decrease mortality in children by increasing health care utilisation. The authors point out that in most cases, poor people are prevented from accessing health care due to out-of-pocket payments. A cross-sectional study which employed electronic data on the status of health insurance, health care utilisation and child mortality for children under five was conducted. Multi-variate logistic regressions were conducted to control for confounding factors. The study's results indicate that 71% of children in Uganda were uninsured, 10% were fully insured for the duration of the study while 19% were insured for a while during the study period. Of these children, the risk of dying for children who were insured reduced by 36%, while they were also at a lower risk of malnutrition compared to the uninsured children.

Anaba *et al.,* (2020) studied the relationship between health insurance membership and anaemia in children under 5 years in Ghana. Their explanatory variable was exposure to health insurance and their outcome variable was anaemia status amongst children. Anaemia status in children was measured as having haemoglobin levels below or equal to 10.9g/dl and these children were said to be anaemic. The authors employed a binary logistic regression which controlled for confounding factors such as mother's education and child's age. Their results indicate that approximately 57% of Ghanaian children under 5 years of age had anaemia and of these children, the majority (i.e. 73%) did not have health insurance. The authors further find that health insurance is a protective factor against anaemia among children under the age of five.

Howell *et al.,* (2010) find that the expansion of Medicaid and SCHIP (i.e. State Children's Health Insurance Program) insurance in the United States of America reduced child mortality per 1,000 live births. Peng and Conley (2016) used longitudinal household data from the year 2000 to 2009 in China to study the impact of health insurance on child health. The authors used ordinary least squares regressions, instrumental variables, and difference in differences to study the relationship. Peng and Conley (2016) used malnutrition and HAZ score as measures of child health outcomes. There was a similar trend in the results which all showed an improvement in child health after enrolling in the New Rural Cooperative Medical Scheme (NCMS). The scheme had a greater impact on infants between birth and 5 years of age.

Wasting amongst children under 5 years of age is also a problem in Sub-Saharan African countries like Ghana. Darteh *et al.,* (2017), examined the determinants of wasting in children under 5 years of age in Ghana. The authors used Ghana's Demographic and Health Survey conducted in 2014 for the examination. The study's outcome variable was wasting and was measured as weight-for-age for children below the age of 5. The authors conducted bi-variate regression and multi-variate regression analysis. The bi-variate results indicated no statistically significant relationship between wasting and health insurance. In contrast, a multi-variate regression analysis indicated a statistically significant relationship between health insurance and wasting. The descriptive statistics showed that around 68% children were registered for health insurance and amongst these, the chances of being wasted were very low compared to those who were uninsured. These results imply that if access to health insurance to the uninsured children in Ghana is increased, there would be an improvement in child health outcomes and specific in this case wasting. The authors also infer that the differences between the insured and uninsured are a result of the insured having easier access to health care services than the uninsured.

3. Methods

3.1. Data

This study does not involve collecting primary data, it uses secondary data collected by the Human Sciences Research Council (HSRC). The data to be used in this study was obtained under a user's agreement with the HSRC. This data will not be used for any other purposes except for the ones mentioned in this research paper. This study uses data collected in

2011/2012 as part of the South African National Health and Nutrition Examination Survey (SANHANES-1) for children between the ages of 0-14 years. The SANHANES-1 survey is a continuous population health survey with the aim of addressing the changing health needs in the country and impart more comprehensive platform to study the nation's health status regularly (Shisana *et al.,* 2013). The SANHANES-1 contains important information to assist in mapping the emerging non-communicable diseases in South Africa and allow for their social, economic, behavioural and environmental determinants analysis (Shisana *et al.,* 2013). The proposed dependent variable for this study is child health outcomes which will be proxied by stunting, wasting, vitamin A status, anaemia, diarrhoea, fever and cough. The measurement of these child health outcomes as recommended by WHO, SANHANES-1 child questionnaire and child examination form, are shown in Table 2. The choice for multiple outcome variables is to allow for the evaluation of whether financial protection affects some health outcomes and not others or if it affects the outcomes in the same manner.

Health insurance is often used to measure financial protection. However, enrolling in a health insurance scheme does not guarantee financial protection because there may still be costs associated with accessing health care services. These costs include co-payments, co-insurance and deductibles. Those with health insurance may find it hard to pay for the previously mentioned costs and are therefore not completely financially protected (Gaffney *et al.,* 2020). This study, unlike most studies that focus on health insurance as the only means of financial protection, will focus on three proxies for financial protection. Included in the SANHANES-1 survey's visiting point (household) questionnaire are two questions, one which relates to affordability of healthcare and one on having health insurance. These questions will be used as binary variables taking the value of 0 and 1 (i.e. 1 if the households can afford health care services and 0 if they cannot afford health care services, and 1 if households have health insurance and 0 if they do not have health insurance).

The effects of strong financial protection are investigated by constructing a binary variable which takes the value of 1 if a household has health insurance and does not find it difficult to afford the necessary healthcare services and takes the value of 0 if a household does not belong to any health insurance or finds it difficult to afford the necessary health care services. This will be the third treatment of this study. These questions from the visiting point questionnaire are shown in Table 3. Being able to afford costs associated with accessing health care services will be regarded as being financially protected and not being able to afford the cost of necessary care will constitute not being financially protected. Similarly, having health insurance will be referred to as being financially protected and not having health insurance will be deemed as not being financially protected.

Table 2: Child health outcomes

Indicators	Measurement
Stunting	As defined by the WHO, stunting is measured as being under 5 years of age with more than 2 standard deviations below the median height-for-age reference value
Wasting	As defined by the WHO, wasting is measured as being under 5 years of age with more than 2 standard deviations below the median weight for-height reference value
Vitamin A status	As defined by the WHO, vitamin A status is measured as follows: Vitamin A deficient: serum retinol concentration < 0.70 µmol/L (Yes=1). Vitamin A sufficient: serum retinol concentration ≥ 0.70 µmol/L (No=0).
Anaemia	The presence of anaemia (Hb < 11 g/dL) as a problem of public health significance can be classified as follows (WHO/CDC 2008): Iron deficiency anaemia: Hb < 11 g/dL (Yes=1) Iron depletion/deficiency: Hb ≥ 11 g/dL (No=0)
Diarrhoea	In the last two weeks, has (Name) had diarrhoea? Responses: (i.e. Yes=1, No=0)
Fever/ Cough	At any time in the last two weeks, has (NAME) been ill with a fever? Responses: (i.e. Yes=1, No=0) OR At any time in the last two weeks, has (NAME) had an illness with a cough? Responses: (i.e. Yes=1, No=0)

(Source: WHO, 2008, SANHANES-1, 2011-2012)

Table 3: Proxies of Financial Protection

Proxy	Question
Health Insurance	1. Do you have private medical aid / health insurance either in your own name or through another family member? Responses: Yes, in own name (=1); Yes, through a family member (=1); No (=0)
Affordability	2. In the past 12 months, have you had difficulty affording the cost of necessary medical care? Responses: Yes (=0); No (=1)
Strong financial protection	3.Do you have private medical aid/health insurance either in your own name or through another family member? Response: Yes, in own name or yes through a family member (=1) In the past 12 months, have you had difficulty affording the cost of necessary medical care? Responses: No (=1) Do you have private medical aid / health insurance either in your own name or through another family member? Responses: No (=0)

In the past 12 months, have you had difficulty affording the cost of necessary medical care? Responses: Yes (=0)

(Source: SANHANES-1, 2011-2012)

3.2. Methodology

This study uses Propensity Score Matching (PSM) to evaluate the impact of financial protection on child health outcomes. Propensity score matching will be performed at the household level. This method allows for the search of households with and without financial protection that have similar observable characteristics (Rosenbaum & Rubin, 1983). The PSM method selects individuals that are similar in all aspects with those in the treatment group except for financial protection, and this allows the control and treatment group to be comparable (Rosenbaum & Rubin, 1983). PSM is suitable for this study because it reduces selection bias when estimating the exact treatment effect as compared to other econometric approaches (Littnerova *et al.,* 2013). PSM balances observed characteristics in the sample and ensure that treatment is random and therefore reduces selection bias. This balanced dataset, enables a direct comparison of baseline covariates between the treated and untreated children. Matching of the treatment and control group will be based on the propensity score.

The treatment in this study will be the enrolment into health insurance, the affordability of health services, or ‘strong’ financial protection, as explained previously. The treatment group will be classified by whether an individual has health insurance or can afford health care services, and the control group will be those that do not have health insurance, cannot afford health care services or having or not having strong financial protection. There are other covariates that may measure financial protection and influence the decision to take-up health insurance. These covariates include the household head’s employment status, the household head’s age, race, and sex, the household head’s marital status, geography (urban or rural), the household head’s level of education, and the household’s wealth index (Chen & Chu, 2019; Anaba *et al.,* 2020; Govendor *et al.,* 2014; Howell *et al.,* 2010 & Peng & Conley, 2016). The decision to include these observable characteristics was influenced by literature and multiple attempts to balance the treatment and outcome models.

The household head’s income was measured in the visiting point questionnaire, and it was categorised from 0 to 13 (i.e. 0 referred to having no income and 13 referring to refusal to answer the income question). There was, however, high non-response to this question about income and making it unlikely to be a good measure of socioeconomic status. The wealth index was used instead of household income because it is considered a reliable measure of socioeconomic status in most developing countries (Gordon, Booysen & Mbonigaba, 2020). The wealth index was computed using 16 variables which included the type of housing, access to water and sanitation services, and if the household owned 13 household assets. The wealth index quintiles were then computed by applying Multiple Correspondence Analysis (MCA) to the household survey data. These socio-economic and demographic characteristics are employed to balance the study's sample of the treatment and control groups.

Two groups are identified: household with financial protection and denoted $T_i = 1$ for household i and those without financial protection denoted $T_i = 0$. In this model $Y1_i$ and $Y0_i$ are two potential outcomes for household with and without financial protection. The treatment effect will be the difference between the two potential outcomes such that: $Y = Y1_i - Y0_i$. Households either have financial protection or do not have financial protection. Therefore only $Y1_i$ or $Y0_i$ is observed at a time not both. Therefore, it is infeasible to compute treatment effects because of the missing potential outcome. In this case, let the treatment dummy be $T = 1$ for those with financial protection and $T = 0$ for those without financial protection. Let $Y_i = Y1_iT + Y0_i(1 - T)$ represent the observed outcome for households with financial protection. In this case only one potential outcome is realised, and the unprotected potential outcome is not realised.

The difference in outcomes is thus $E(Y_i|T = 1) - E(Y_i|T = 0)$. Therefore, the average treatment on the treated (ATT) will be: $ATT = E(Y1_i|T = 1) - E(Y0_i|T = 1)$. However, this average treatment on the treated includes selection bias. For example, a risk averse individual who is not severely sick may self-select into getting health insurance although they are healthy. In contrast, a highly sick individual with poor health may self-select into enrolling for health insurance. Alternatively, purchasing a private health insurance is not random. Those in the formal sector may be encouraged and subsidised by their employers to enrol whilst those in the informal sector and unemployed may not afford to purchase a private health insurance. Therefore, $E(Y0_i||T = 1) - E(Y0_i|T = 0)$ is not equal to zero due to selection bias. The two groups (i.e. financially protected and unprotected financially) are not comparable, and this may yield biased estimates of ATT. Ideally randomisation is applied to eliminate selection bias when using randomised control trials. Randomisation makes the treatment and control group comparable such that $ATT = E[Y0_i|T = 1] = E[Y0_i|T = 0]$. Usually a t-test would yield unbiased estimates when using RCT's. However, this is a non-experimental study and can therefore not use RCT's.

For matching, Stata routine psmatch2 is used and logit models are applied to determine propensity scores. The logit model probability can be stated as: $\Pr(T = 1) = \Pr(u < \beta x) = \frac{e^{\beta x}}{1+e^{\beta x}}$. The propensity score for the i^{th} household will be denoted $ps_i = \Pr(T_i = 1) = \frac{e^{\hat{\beta} x}}{1+e^{\hat{\beta} x}}$ (i.e. $\hat{\beta}$ is from the estimated logit model). Psmatch2 is provided for by Lueven and Sianesi (2003) and provides for the implementation of various types of matching estimators and matching algorithms. This includes the nearest neighbour matching, kernel matching, calliper radius matching and local linear regression matching. It is advantageous to use this programme because it includes routines for covariate imbalance testing and the attainment of standard errors through bootstrapping.

Since this is a non-experimental study, PSM requires for two assumptions to hold. The first assumption is confoundedness, i.e. it requires that all relevant variables to the probability of receiving treatment be observed and included in covariates and it rules out self-selection based on unobservable factors (Rosenbaum & Rubin, 1983). This assumption also allows for the control group to be used as an unbiased counterfactual for the treatment group. The second assumption is common support or the degree of overlap. This assumption necessitates a positive probability of being assigned to each treatment state for all covariates (Rosenbaum & Rubin, 1983). It ensures that there is adequate overlap in the characteristics of the treatment and control group to find adequate matches.

The “pstest” is conducted to check whether the estimated propensity score adequately balances the characteristics between the treated and untreated groups. Pstest is important as it tests if balancing is successful, and it also gives an output of a criteria that is used to check the quality of matching (Caliendo & Kopeinig, 2008). The criteria includes mean standardised bias test, t-tests, joint significance, Pseudo- R^2, Rubin’s B and R (Rubin, 2001). The joint significance test includes the p-values of the likelihood ratio test which necessitates that all covariates should be statistically insignificant, the mean bias which represents the distribution of bias, which ought to be less than or equal to 5%, Rubin’s B and R which show the overall level of bias and the absolute standardised difference of the means of the linear index of the propensity score in both treatment and control groups and the ratio of the treated to non-treated variances of the propensity score indexes (Caliendo & Kopeinig, 2008). Post-matching, there should not be any statistically significant differences between covariate means of the treated and untreated as per the joint significance test. Rubin’s B and R have predetermined values that ought to be obtained for the model to be sufficiently balanced and for B it is 25 and R must be in the range of 0.5 and 2 (Rubin, 2001).

4. Analysis

4.1. Descriptive statistics

Table 4: Descriptive statistics

Variables	**Mean**	**Standard deviation**
Outcome Variables		
Anaemia	0.070	0.255
Cough	0.338	0.473
Fever	0.287	0.453
Diarrhoea	0.105	0.307
Vitamin A status	0.423	0.494
Stunting	0.177	0.382
Wasting	0.037	0.188
Treatment variables		
Medical aid	0.153	0.359
Affordability	0.694	0.461
Strong Financial Protection	0.716	0.496
Explanatory covariates		
Wealth index quintiles		
Wealth index quintile 1 (poorest)	0.247	0.431
Wealth index quintile 2	0.201	0.401
Wealth index quintile 3	0.206	0.405
Wealth index quintile 4	0.198	0.398
Wealth index quintile 5 (richest)	0.145	0.352
Household head’s employment status		
Employed	0.439	0.496
Unemployed	0.560	0.496
Household head’s educational status		
No schooling	0.164	0.371
Primary education	0.313	0.463
Secondary education	0.513	0.463
Tertiary education	0.008	0.093
Reliance on Public sector for health care services	0.773	0.418
Demographics		
Child age	6.847	4.172
Household head’s age	49.104	14.749
Female	0.498	0.500
Race		
African	0.742	0.437
White	0.025	0.158
Coloured	0.184	0.388
Indian	0.044	0.206
Other races	0.002	0.050

Marital status (yes/no)	0.488	0.499
Geographical location		
Urban Formal	0.451	0.497
Urban informal	0.144	0.351
Rural informal (i.e., tribal)	0.269	0.443
Rural formal (i.e., farms)	0.134	0.340

Table 4 shows the means and standard deviations for all variables used in this study. The outcome variables are highlighted, followed by the treatment variables and the observable characteristics that were used for matching. The SANHANES-1 data shows that on average 7% of children had anaemia, 33,8% had a cough, 28.7% had fever, 10.5% had diarrhoea, 42.3% had vitamin A deficiency, 17.7% were stunted and 3.7% were wasted. There are approximately 15% of children who lived in households with access to health insurance, 69.4% who did not find it difficult to afford the necessary health care services and 71.6% who had strong financial protection. This is expected considering that Govendor *et al.,* (2014) states that approximately 20% of the population in South Africa has health insurance and majority rely on the public sector. If the household reported not to have health insurance, they were asked in the visiting point questionnaire if they used any of the following options: paying out of pocket or relying on the public sector for health care services. A binary variable was created where 1 referred to relying on the public sector and 0 referred to those that pay out of pocket. The vast majority of the households show that they did not have any difficulties affording the necessary health care services and the reason for this may be the fact that primary health care services are free for children and only inpatient care requires minimal charges. The latter statement can be supported by looking at the mean reliance on the public health care sector for health care services and it shows that approximately 77.3% households were reliant on the public sector for health care services.

The wealth index quintiles are arranged from the poorest to the richest (i.e. wealth index quintile 1 is associated with being the poorest). Approximately, 24.7% of the households were classified as being the poorest and 14.5% were the richest. The average age for children in this study is 6 years whilst the average household head's age is 49 years and of these household heads, 51.3% had secondary education, 16.4% had no schooling, 0.8% had tertiary education and 56% were unemployed. Approximately 48.8% of the household heads were married. On average, 49,8% children were females, and of the children, 74.2% were African, 2.5% were White, 18.4% were Coloured, 4% were Indian and 0.2 reported to be of other races. Many households resided in the urban formal geographical location with the average of 45.1% followed by rural informal settlements with an average of 26.9%, urban informal with 14.4%

and rural formal with 13.4%. These statistics reflect the demographics and health for South African children between the ages of 0 and 14.

Table 5: Outcomes, by sex

Outcome variables	Female mean	Male mean	Mean differences	Standard errors	P value Ha: diff! =0	T Test
Anaemia	0.066	0.072	-0.005	-0.010	0.588	0.540
Cough	0.324	0.348	-0.024	-0.019	0.203	1.271
Fever	0.288	0.286	0.002	0.018	0.911	-0.110
Diarrhoea	0.100	0.113	-0.013	-0.012	0.262	1.121
Vitamin A	0.379	0.463	-0.084	-0.037	0.023	2.266
Stunting	0.159	0.194	-0.035	-0.011	0.002	3.050
Wasting	0.028	0.044	-0.015	-0.005	0.005	2.769

The prevalent childhood health indicators may or may not vary across sex. The null hypothesis states that there are no statistically significant differences between the means of these childhood health indicators across the sex of the child. To test this null hypothesis, a Stata routine "ttest" was conducted. This test allows for the comparison of means of the same outcome variable between the sex of the children. Assuming that the variance of the males and females are the same, the results are shown in Table 5. The prevalence of anaemia, fever, diarrhoea and coughing shows to be lower in females than it is in males, however the differences are not statistically significant. The null hypothesis is not rejected for anaemia, diarrhoea, fever, and coughing. This implies that there is no statistically significant difference in the mean of males and females.

There are statistically significant differences in means for the outcome variables vitamin A, stunting and wasting and they show that the prevalence of these childhood illnesses is lesser in females than males. This finding is inconsistent with the null hypothesis, and we therefore reject the null hypothesis. Although it is statistically insignificant, the prevalence of fever is higher in males than it is in females. These results show that these childhood health outcomes affect the health of children in different ways and which sex is most likely to be affected more by the illness. This necessitates the investigation on whether the differences may be explained by differences in the extent of financial protection, and this is conducted in the next section.

4.2. Results

Table 6a: Treatment effects – treatment is proxied by health insurance

	Anaemia	Cough	Fever	Diarrhoea	Vitamin A Deficiency	Wasting	Stunting
Matching algorithm A: Nearest neighbour							
ATT	0.054	0.100	-0.020	0.047	0 .125	-0.005	0.022
	(1.41)	(1.48)	(0.30)	(1.24)	(0.81)	(-0.19)	(0.58)
ATE	0.105	0.081	-0.032	0.045	0.154	0.044	0.082
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	X	√	√	√
Mean bias	X	X	X	X	X	X	X
B	X	X	X	X	X	X	X
R	√	√	√	√	√	√	√
No.Obs	1 455	1 515	1 519	1 519	430	2 597	2 597
Matching algorithm B: Calliper Radius							
ATT	0.035	0.121	0.020	0.003	0.074	-0.006	-0.015
	(1.00)	(2.21)	(0.41)	(0.09)	(0.57)	(-0.33)	(-0.48)
ATE	0.040	0.103	0.016	0.035	0.208	0.027	0.019
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	√	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	X	√	√
B	√	X	X	X	X	√	√
R	√	X	X	X	X	√	√
No. Obs	1 455	1 515	1 519	1 519	430	2 597	2 597
Matching algorithm C: Kernel							
ATT	0.030	0.081	-0.021	0.016	-0.002	-0.000	-0.035
	(0.92)	(1.59)	(-0.46)	(0.48)	(-0.02)	(-0.01)	(-1.17)
ATE	0.020	0.106	0.010	-0.002	0.161	0.015	-0.008
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	X	√	√
B	√	√	√	√	X	√	√
R	√	√	√	√	X	√	√
No. Obs	1 455	1 515	1 519	1 519	430	2 597	2 597
Matching algorithm D: Local linear regressions							
ATT	0.024	0.085	-0.010	0.018	-0.057	0.002	-0.039
	(0.63)	(1.26)	(-0.15)	(0.49)	(-0.37)	(0.09)	(-1.04)
ATE	0.034	0.103	0.002	-0.004	0.172	0.026	0.024
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	X	√	√	√

Mean bias	X	X	X	X	X	X	X
B	X	X	X	X	X	X	X
R	√	√	√	√	√	√	√
No. Obs	1 455	1 515	1 519	1 519	430	2 597	2 597

Note: These are unweighted results. The T-statistics is reported in the parentheses and "n.r" denotes the t-statistics that STATA could not estimate. No. obs refers to the number of observations or sample size.

Health insurance, affordability, and being able to have health insurance and not finding it difficult to afford the necessary health care services are deemed to be the most important aspects of reducing childhood morbidity and mortality arising from childhood illnesses (Govendor *et al.*, 2014; Chen & Chu, 2019). The treatment effects of these three treatment proxies (i.e., health insurance, affordability, and 'strong' financial protection) are tabulated in Tables 6a to 6c. The tick on the 5 criteria to determine the quality of matching and successful balancing indicates that that specific criterion is met, and the "X" indicates when a specific criterion has not been met. The t-test reported is from the psmatch2 output and is directly associated with the treatment effects. It explains if the treatment effect is statistically significant or not and we can therefore reject the null hypothesis or not reject it.

To check the sensitivity of the treatment effects, four matching algorithms were tested. The tested matching algorithms include nearest neighbour (i.e. neighbour=1), calliper radius (radius=0.01), kernel (default 0.6 bandwidth) and local linear regression. Moreover, to check if treatment affects some childhood diseases in the same manner or not 7 child health outcomes were tested for each of the three treatment proxies. As stated in Rosenbaum & Rubin (1983) and Rubin (2001)), a model is sufficiently balanced when it has a Rubin's R value that is between 0.5 and 2 and Rubin's B that is less than or equal to 25. For the purposes of this study and as per Rubin (2001), weak balance refers to the balancing where the required values for Rubin's R and B are not met. Strong and sufficient model balance occurs when Rubin's R and B values are met.

Table 6a shows the treatment effects of having health insurance (i.e. as a proxy for financial protection) across four matching algorithms. The results for nearest neighbour are statistically insignificant for all outcomes. The average treatment effect on the treated shows that having health insurance increases the prevalence of anaemia, cough, vitamin a deficiency, and stunting by approximately 5.4%, 10%, 4.7%, 12.5% and 2% respectively. Similarly, the average treatment effect shows that health insurance increases the prevalence of the abovementioned health outcomes including wasting. The models presented here do not, however, show strong balance of covariates. This is because, although the condition for Rubin's R values is met, the overall level of bias (i.e. Rubin's B) exceeds 25.

Health insurance is shown to reduce fever and wasting as per the ATT results. The calliper radius results show an improvement in the balancing of covariates for anaemia, wasting and stunting models as both Rubin's R and B values are met; however, the ATT results resemble those reported for nearest neighbour. In contrast, coughing is statistically significant in this case and shows that health insurance increases the prevalence of coughing. Although statistically insignificant, both ATT and ATE show that having health insurance decreases the prevalence of wasting and stunting. Kernel matching results indicate that no treatment effect is statistically significant. Health insurance decreases the prevalence of fever, vitamin A deficiency, wasting and stunting by approximately 2.1%, 0.2%, 0.006% and 3.5% respectively, whilst increasing the prevalence of anaemia, cough, and diarrhoea by approximately 3%, 8% and 1.6% respectively. The local linear regression model resembles the nearest neighbour model where most of the criterion of quality matching like Rubin's B and LR-test is not met. The results show that health insurance decreases the prevalence of fever, vitamin A deficiency and stunting, whilst increasing that of anaemia, cough, diarrhoea and wasting.

Table 6b: Treatment effects- treatment is proxied by affording the cost of necessary health care

	Anaemia	Cough	Fever	Diarrhoea	Vitamin A Deficiency	Wasting	Stunting
	Matching algorithm A: Nearest neighbour						
ATT	-0.030 (-1.33)	-0.084 (2.08)	-0.130 (3.39)	0.009 (0.38)	0.056 (0.84)	0.010 (1.08)	-0.026 (-0.83)
ATE	-0.020 (n.r)	-0.083 (n.r)	-0.117 (n.r)	0.007 (n.r)	0.062 (n.r)	0.009 (n.r)	-0.016 (n.r)
t-test	X	√	√	X	X	X	X
LR-test	X	√	√	√	√	X	X
Mean bias	√	√	√	√	X	√	√
B	X	√	√	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	1 429	1 475	1 481	1 480	423	2 530	2530
	Matching algorithm B: Calliper radius						
ATT	-0.023 (-1.33)	-0.094 (-3.08)	-0.105 (-3.55)	-0.010 (-0.53)	0.037 (0.67)	0.006 (0.74)	-0.009 (-0.53)
ATE	-0.017 (n.r)	-0.098 (n.r)	-0.111 (n.r)	-0.006 (n.r)	0.046 (n.r)	0.007 (n.r)	-0.013 (n.r)
t-test	X	√	√	X	X	X	X
LR-test	√	√	√	√	√	√	√

Mean bias	√	√	√	√	√	√	√
B	√	√	√	√	√	√	√
R	√	√	√	√	√	√	√
No. Obs	1 429	1 475	1 481	1 480	423	2 530	2530
Matching algorithm C: Kernel							
ATT	-0.020	-0.092	-0.102	-0.005	0.014	0.008	-0.011
	(-1.23)	(-3.12)	(-3.58)	(-0.27)	(0.27)	(1.03)	(-0.66)
ATE	-0.015	-0.092	-0.106	-0.003	0.019	0.009	-0.014
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	√	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	√	√	√
B	√	√	√	√	√	√	√
R	√	√	√	√	√	√	√
No. Obs	1 429	1 475	1 481	1 480	423	2 530	2530
Matching algorithm D: Local linear regressions							
ATT	-0.028	-0.097	-0.106	-0.011	0.023	0.004	-0.012
	(-1.23)	(-2.42)	(-2.77)	(-0.46)	(0.36)	(0.47)	(-0.54)
ATE	-0.021	-0.096	-0.109	-0.008	0.024	0.008	-0.015
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	√	√	X	X	X	X
LR-test	X	√	√	√	√	X	X
Mean bias	√	√	√	√	X	√	√
B	X	√	√	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	1 429	1 475	1 481	1 480	423	2 530	2 530

Note: These are unweighted results. The T-statistics is reported in the parentheses and "n.r" denotes the t-statistics that STATA could not estimate. No. obs refers to the number of observations or sample size.

Table 6b reports the treatment effects on the treated and average treatment effects of being able to afford the cost of necessary health care services as treatment proxy and not being able to afford the cost of necessary health care services as the control group across four matching algorithms. The nearest neighbour model shows that matching quality and balancing was achieved except for anaemia and vitamin A deficiency where Rubin's B condition was not met. Coughing and fever models show statistically significant treatment effects and met all the matching and balancing criterion. The ATT results indicate that being able to afford the cost of necessary health care services decreases the prevalence of anaemia, coughing, fever and stunting by approximately 3%, 8%, 13% and 2.6% respectively. The average treatment effect shows a decrease for the four outcome models as well. Similarly, calliper radius shows strongly and sufficiently balanced models and shows decreasing average treatment effects on the treated for anaemia, cough, fever, diarrhoea and stunting by approximately 2.3%, 9%, 10.5%, 1% and 0.9% respectively. The calliper radius matching algorithm shows that all outcome models met Rubin's R and B conditions, pass the LR-test and the mean bias is below 5%. The treatment effects are, however, statistically insignificant except for coughing and fever.

The Kernel matching algorithm shows strong quality of matching and sufficient balancing of covariates as four matching criteria are met for all outcome models and the treatment effects on the treated are statistically insignificant for all outcome models except coughing and fever. Treatment effect on the treated decreases the prevalence of anaemia, coughing, fever, diarrhoea and stunting by approximately 2%, 9.2%, 10.2%, 0.5% and 1.1% respectively. The local linear matching algorithm is sufficiently balanced for all outcome models except for anaemia and vitamin A deficiency as they do not meet Rubin's R and B conditions. Like the other three matching algorithms, coughing and fever are statistically significant and show that being able to afford the necessary health care services results in the reduction in the prevalence of these two childhood illnesses. In contrast, the average treatment effect on the treated indicate an increase in the prevalence of wasting and vitamin A deficiency consistently in all four matching algorithms.

Table 6c: Treatment effects where treatment is proxied by having strong financial protection

	Anaemia	Cough	Fever	Diarrhoea	Vitamin A Deficiency	Wasting	Stunting
			Matching algorithm A: Nearest neighbour				
ATT	-0.015	-0.059	-0.067	0.034	0.048	0.010	-0.016
	(-0.67)	(-1.40)	(-1.57)	(1.34)	(0.71)	(0.94)	(-0.67)
ATE	-0.014	-0.061	-0.085	0.033	0.043	0.010	-0.017
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	X	X	X	X	√	X	X
Mean bias	√	√	X	√	X	√	√
B	√	X	X	X	X	√	√
R	√	√	√	√	√	√	√
No. Obs	1 427	1 478	1 484	1 483	423	2 530	2 530
			Matching algorithm B: Calliper radius				
ATT	-0.032	-0.052	-0.075	0.020	0.014	0.012	-0.017
	(-1.79)	(-1.54)	(-2.25)	(0.92)	(0.26)	(0.070)	(-0.90)
ATE	-0.024	-0.058	-0.083	0.019	0.009	0.012	-0.017
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)

t-test	X	X	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	√	√	√
B	√	√	√	√	√	√	√
R	√	√	√	√	√	√	√
No. Obs	1 472	1 478	1 484	1 483	423	2 530	2 530
Matching algorithm C: Kernel							
ATT	-0.027	-0.053	-0.089	0.016	0.007	0.015	-0.015
	(-1.61)	(-1.66)	(-2.81)	(0.80)	(0.15)	(1.92)	(-0.81)
ATE	-0.020	-0.060	-0.092	0.015	0.011	0.014	-0.017
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	√	√	√
B	√	√	√	√	√	√	√
R	√	√	√	√	√	√	√
No.Obs	1 427	1 478	1 484	1 483	423	2 530	2530
Matching algorithm D: Local linear regressions							
ATT	-0.040	-0.056	-0.091	0.009	0.018	0.015	-.018
	(-1.75)	(-1.34)	(-2.13)	(0.38)	(0.27)	(1.40)	(-0.72)
ATE	-0.030	-0.059	-0.093	0.010	0.019	0.016	-0.019
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	√	X	X	X	X
LR-test	X	X	X	X	√	X	X
Mean bias	√	√	X	√	X	√	√
B	√	X	X	X	X	√	√
R	√	√	√	√	√	√	√
No. Obs	1 427	1 478	1 484	1 483	423	2 530	2530

Note: These are unweighted results. The T-statistics is reported in the parentheses and "n.r" denotes the t-statistics that STATA could not estimate. No. obs refers to the number of observations or sample size.

Table 6c reports treatment effects (i.e. ATT and ATE) when financial protection is proxied by having strong financial protection. The nearest neighbour model shows weak balance for some health outcome models and there are no statistically significant results. Rubin's B statistic condition is not met for coughing, fever, diarrhoea and vitamin A deficiency outcome models and the LR-test was only met for vitamin A deficiency. This means that after matching, there were covariates that remained statistically significant for the other treatment/outcome models except vitamin A deficiency. The ATT results indicate that having strong financial protection reduces the prevalence of anaemia, coughing, fever and stunting by 1.5%, 5,9%, 6.7% and

1,6% respectively and increases the prevalence of diarrhoea, vitamin A deficiency and wasting by approximately 3.4%, 4.8% and 1% respectively.

The ATE results indicate that strong financial protection reduces the prevalence of anaemia, coughing, fever and stunting. The calliper radius and kernel models are strongly and sufficiently balanced and they have good matching quality as most outcome models met the LR-test, mean bias, Rubin's B and R conditions and show fever as statistically significant and has negative relationship with strong financial protection for both ATE and ATT. This means that having strong financial protection results in a reduction in the prevalence of fever. Strong financial protection also reduces anaemia, coughing, fever and stunting whilst increasing diarrhoea, vitamin A deficiency and wasting in both models. The latter results are, however, statistically insignificant. The local linear results resemble those of nearest neighbour with weak balancing and poor quality of matching as Rubin's R and B statistics conditions are not met for coughing, fever, diarrhoea and vitamin A deficiency. The results except for fever, are statistically insignificant results and indicate a negative relationship between strong financial protection and anaemia, cough, fever (i.e. statistically significant) and stunting whilst showing an increase in diarrhoea, wasting and vitamin a deficiency.

Table 7a: Treatment effects by sex (Health Insurance)

	Anaemia	Cough	Fever	Diarrhoea	Vitamin A Deficiency	Wasting	Stunting
Matching algorithm A: Nearest neighbour							
Males							
ATT	0.035 (0.65)	0.166 (1.88)	-0.088 (-1.00)	-0.101 (-1.55)	-0.352 (-1.58)	0.029 (0.92)	-0.038 (-0.64)
ATE	0.065 (n.r)	0.133 (n.r)	0.059 (n.r)	-0.042 (n.r)	0.148 (n.r)	0.005 (n.r)	0.224 (n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	X	X	X	X	X	X	X
B	X	X	X	X	X	X	X
R	√	√	√	√	X	√	√
No. Obs	744	762	764	764	215	1 276	1 276
Females							
ATT	0.028 (0.52)	0.052 (0.52)	-0.035 (-0.36)	0.107 (1.73)	0.285 (1.04)	0 (0.00)	-0.012 (-0.23)
ATE	-0.033 (n.r)	0.092 (n.r)	-0.022 (n.r)	-0.031 (n.r)	0.362 (n.r)	0.044 (n.r)	0.011 (n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√

Mean bias	X	X	X	X	X	X	X
B	X	X	X	X	X	X	X
R	√	√	X	√	√	√	√
No. Obs	599	751	753	753	73	1 321	1 321
Matching algorithm B: Calliper radius							
Males							
ATT	0.014	0.128	-0.015	-0.059	-0.059	0.036	-0.022
	(0.28)	(1.67)	(-0.23)	(-1.38)	(-0.29)	(1.21)	(-0.45)
ATE	0.110	0.106	0.066	-0.032	0.240	0.031	0.090
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	X	√	√	X	X	X	X
B	X	√	√	√	X	X	X
R	√	X	X	X	√	√	√
No. Obs	744	762	764	764	215	1276	1 276
Females							
ATT	0.016	.159	0.027	0.120	0.305	-0.023	-0.043
	(0.32)	(1.97)	(0.38)	(1.90)	(1.17)	(-1.03)	(-0.96)
ATE	-0.026	0.104	-0.008	-0.006	0.356	0.012	-0.050
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	X	√	X	X	X	X
B	√	X	X	X	X	X	X
R	√	√	√	√	√	√	√
No. Obs	599	751	753	753	73	1 321	1 321
Matching algorithm C: Kernel							
Males							
ATT	0.042	0.110	-0.006	-0.024	-0.083	0.027	-0.035
	(0.89)	(1.57)	(-0.10)	(-0.55)	(-0.52)	(0.99)	(-0.84)
ATE	0.068	0.114	0.059	-0.025	0.114	0.014	0.013
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	X	√	√
B	√	√	√	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	744	762	764	764	215	1 276	1 276
Females							
ATT	0.014	0.077	0.018	0.078	0.224	-0.033	-0.048
	(0.31)	(0.93)	(0.24)	(1.31)	(0.99)	(-1.54)	(-1.12)
ATE	-0.012	0.104	-0.082	0.012	0.319	0.012	-0.048
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)

t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	X	X	X	X	X	X
B	√	X	X	X	X	X	X
R	√	√	√	√	X	√	√
No. Obs	599	751	753	753	73	1 321	1 321
Matching algorithm D: Local linear regressions							
Males							
ATT	0.033	0.100	0.002	-0.021	-0.207	0.026	-0.038
	(0.61)	(1.13)	(0.03)	(-0.33)	(-0.93)	(0.83)	(-0.63)
ATE	0.128	0.125	0.075	-0.011	0.153	0.031	0.052
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	X	X	X	X	X	X	X
B	X	X	X	X	X	X	X
R	√	√	√	√	X	X	√
No. Obs	744	762	764	764	215	1 276	1 276
Females							
ATT	0.015	0.063	0.025	0.071	0.189	-0.030	-0.044
	(0.29)	(0.63)	(0.26)	(1.15)	(0.69)	(-1.18)	(-0.78)
ATE	-0.031	0.084	-0.073	-0.012	0.422	0.017	-0.016
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	X	X	X	X	X	X	X
B	X	X	X	X	X	X	√
R	√	√	X	√	√	√	√
No. Obs	599	751	753	753	73	1 321	1 321

Note: These are unweighted results. The T-statistics is reported in the parentheses and "n.r" denotes the t-statistics that STATA could not estimate. No. obs refers to the number of observations or sample size.

It was established that child health outcomes differed by sex and there is less prevalence of these illnesses in females. It is, therefore, important to establish if treatment effects differ according to sex or not. Tables 7a-c report average treatment effects and average treatment effects on the treated for male and female children when the treatment is having financial protection through health insurance (Table 7a), affordability (Table 7b), and strong financial protection (Table 7c). The nearest neighbour algorithm in Table 7a is not sufficiently balanced as all outcome models do not meet Rubin's B condition and their mean bias is greater than 5% for both male and female children. The results are all statistically insignificant for ATT and the t-statistic for ATE is missing. Treatment reduces both males and females' health outcomes except for diarrhoea and vitamin A deficiency where treatment seems to reduce its prevalence by 10.1% and 35.3% respectively for males whilst it increases the two child health outcomes by 10.7% and 28.5% respectively in female children.

Calliper radius matching algorithm shows weak balance and low quality of matching for coughing, fever and diarrhoea in males where Rubin's R is not in the range of 0.5 and 2 and anaemia, vitamin A deficiency, wasting and stunting fail to keep the overall bias (i.e. Rubin's B) below 25. The calliper radius matching algorithm shows differences in the effects of treatment for fever and vitamin A deficiency and predicts a negative relationship for males (i.e. treatment reduces the prevalence of fever and vitamin a deficiency in males) and a positive relationship for females (i.e. treatment increases the prevalence of fever and vitamin a deficiency in females). Kernel matching male results show sufficient or strong balance for all outcome models except vitamin A deficiency model, however, there are no statistically significant results. The average treatment effects on the treated results indicate that having health insurance reduces the prevalence of fever, diarrhoea, vitamin A deficiency and stunting in males whilst only reducing wasting and stunting in females. The average treatment effects results do, however, show reductions in the prevalence of anaemia, fever and stunting for females. The local linear regression matching algorithm had weak balance and poor matching quality for both males and females as the outcome models failed to meet Rubin's B condition.

Table 7b: Treatment effects by sex (affordability)

	Anaemia	Cough	Fever	Diarrhoea	Vitamin A Deficiency	Wasting	Stunting
			Matching algorithm A: Nearest neighbour				
			Males				
ATT	0.012 (0.40)	-0.063 (-1.16)	-0.086 (-1.60)	0.026 (0.78)	0.007 (0.07)	0.002 (0.15)	0.008 (0.26)
ATE	0.012 (n.r)	-0.042 (n.r)	-0.084 (n.r)	0.028 (n.r)	-0.014 (n.r)	0.012 (n.r)	0.000 (n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	X	X	√	X	√	√
Mean bias	√	X	X	√	X	√	√
B	√	X	X	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	734	735	738	738	214	1 245	1 245
			Females				
ATT	-0.002 (-0.06)	-0.134 (-2.27)	-0.104 (-1.86)	-0.035 (-0.87)	0.110 (1.15)	-0.010 (-0.88)	-0.062 (-1.90)
ATE	-0.015 (n.r)	-0.145 (n.r)	-0.106 (n.r)	-0.030 (n.r)	0.046 (n.r)	-0.010 (n.r)	-0.050 (n.r)

t-test	X	√	X	X	X	X	X
LR-test	X	√	√	√	√	√	√
Mean bias	X	√	√	X	X	√	√
B	X	X	X	X	X	√	√
R	√	X	√	√	√	√	√
No. Obs	693	735	738	737	209	1 285	1 285
Matching algorithm B: Calliper radius							
Males							
ATT	-0.011	-0.043	-0.087	0.007	-0.016	0.012	0.015
	(-0.49)	(-0.99)	(-2.05)	(0.29)	(-0.20)	(1.03)	(0.56)
ATE	-0.009	-0.039	-0.089	0.016	-0.012	0.019	0.005
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	X	√	√
B	√	√	√	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	734	735	738	738	214	1 245	1 245
Females							
ATT	-0.036	-0.129	-0.107	-0.035	0.062	0.004	-0.022
	(-1.44)	(-3.05)	(-2.59)	(-1.21)	(0.73)	(0.40)	(-0.90)
ATE	-0.026	-0.134	-0.112	-.036	0.036	0.003	-0.027
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	√	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	X	√	√
B	√	√	√	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	693	735	738	737	209	1 285	1 285
Matching algorithm C: Kernel							
Males							
ATT	-0.011	-0.042	-0.096	0.001	-0.007	0.015	0.009
	(-0.50)	(-0.98)	(-2.31)	(0.05)	(-0.09)	(1.25)	(0.34)
ATE	-0.009	-0.035	-0.093	0.012	-0.020	0.018	0.002
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	√	√	√
B	√	√	√	√	√	√	√
R	√	√	√	√	√	√	√
No. Obs	734	735	738	738	214	1 245	1 245
Females							
ATT	-0.032	-0.126	-0.106	-0.030	0.063	0.005	-0.022
	(-1.34)	(-2.89)	(-2.50)	(-1.02)	(0.80)	(0.53)	(-0.95)
ATE	-0.024	-0.135	-0.114	-0.032	0.039	0.003	-0.026
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)

t-test	X	√	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	√	√	√
B	√	√	√	√	√	√	√
R	√	√	√	√	√	√	√
No Obs	693	735	738	737	209	1 285	1 285
Matching algorithm D: Local linear regressions							
Males							
ATT	-0.012	-0.050	-0.091	-0.003	-0.007	0.012	0.004
	(-0.40)	(-0.91)	(-1.69)	(-0.09)	(-0.07)	(0.74)	(0.15)
ATE	-0.011	-0.043	-0.091	0.006	-0.017	0.019	-0.001
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	X	X	√	X	√	√
Mean bias	√	X	X	√	X	√	√
B	√	X	X	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	734	735	738	738	214	1 245	1 245
Females							
ATT	-0.034	-0.129	-0.124	-0.031	0.078	0.002	-0.029
	(-0.99)	(-2.19)	(-2.20)	(-0.78)	(0.82)	(0.22)	(-0.88)
ATE	-0.025	-0.137	-0.127	-0.031	0.057	0.002	-0.032
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	√	√	X	X	X	X
LR-test	X	√	√	√	√	√	√
Mean bias	X	√	√	X	X	√	√
B	X	X	X	X	X	√	√
R	√	X	√	√	√	√	√
No. Obs	693	735	738	737	209	1 285	1 285

Note: These are unweighted results. The T-statistics is reported in the parentheses and "n.r" denotes the t-statistics that STATA could not estimate. No. obs refers to the number of observations or sample size.

Table 7b reports the financial protection effects by sex when treatment is proxied by being able to afford the cost of necessary care. The nearest neighbour matching algorithm shows weak balance for males on anaemia, coughing, fever, diarrhoea, and vitamin A deficiency outcome models due to the failure to meet Rubin's B condition whilst wasting and stunting failed to meet Rubin's R statistic condition. The average treatment effect on the treated for coughing is statistically significant for females and shows a reduction of 13.4%, although coughing is statistically insignificant affordability has a decreasing average treatment effect on the treated of approximately 6.3%. Other health outcomes indicating a reduction include anaemia, fever, diarrhoea, wasting and stunting for females by approximately 0.2%, 10.4%, 3.5%, 1% and

6.2% respectively, whilst coughing and fever were the only two outcomes that saw a reduction for males by approximately 6.3% and 8.6%, respectively. The average treatment effects results also showed a reduction in the prevalence of coughing, fever and vitamin A deficiency for males and a reduction in anaemia, coughing, fever, diarrhoea, wasting and stunting in females.

Calliper radius matching algorithm was strongly balanced and had high quality of matching for both males and females on all outcome models except for vitamin A deficiency. The strong balance is motivated for, by showing sufficient balance which is dependent on meeting Rubin's R and B statistical values. The female average treatment effect on the treated results for fever and coughing were statistically significant and for males only fever was statistically significant. Treatment decreased the prevalence of anaemia, cough, fever, diarrhoea and stunting for females whilst decreasing anaemia, coughing, fever and vitamin A deficiency for males. The kernel matching algorithm was sufficiently balanced for all outcome models, the ATE and ATT results show that treatment reduces the prevalence of anaemia, coughing, fever and diarrhoea for females and reduced the prevalence of anaemia, coughing, fever and vitamin A deficiency in males. The local linear regression matching algorithm was weakly balanced for most outcome models. Only cough, fever and vitamin A outcome models were not sufficiently balanced in males and only wasting and stunting outcome models were sufficiently balanced in females. The male results were not statistically significant meanwhile the female treatment effects for coughing and fever were statistically significant. Financial protection reduced the prevalence of coughing and fever for females by approximately 12.9% and 12.4% respectively.

Table 7c: Treatment effects by sex (strong financial protection)

	Anaemia	Cough	Fever	Diarrhoea	Vitamin A Deficiency	Wasting	Stunting
Matching algorithm A: Nearest neighbour							
Males							
ATT	0.030 (1.10)	-0.029 (-0.51)	-0.131 (-2.15)	0.055 (1.64)	0.074 (0.72)	0.027 (1.80)	-0.008 (-0.25)
ATE	0.012 (n.r)	-0.038 (n.r)	-0.122 (n.r)	0.064 (n.r)	0.052 (n.r)	0.028 (n.r)	1.561 (n.r)
t-test	X	X	√	X	X	X	X
LR-test	√	X	X	X	√	√	√
Mean bias	√	X	X	X	X	√	√
B	X	X	X	X	X	√	√
R	√	√	√	√	√	X	X
No. Obs	735	737	740	740	215	1 247	1 247
Females							
ATT	-0.056	-0.065	-0.143	0.013	0.051	0.004	-0.056

	(-1.80)	(-1.14)	(-2.54)	(0.37)	(0.53)	(0.34)	(-1.75)
ATE	-0.054	-0.085	-0.117	-0.005	0.047	-0.002	-0.058
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	√	X	X	X	X
LR-test	X	X	X	√	√	√	√
Mean bias	X	X	X	X	X	√	X
B	X	X	X	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	690	736	739	738	208	1 283	1 282
Matching algorithm B: Calliper radius							
Males							
ATT	0.008	-0.016	-0.111	0.054	0.046	0.026	0.000
	(0.34)	(-0.34)	(-2.45)	(1.92)	(0.48)	(2.07)	(0.01)
ATE	0.003	-0.008	-0.100	0.058	0.013	0.029	-0.002
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	√	X	X	√	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	X	√	√
B	√	√	√	√	X	√	√
R	√	√	√	√	√	√	√
No. obs	735	737	740	740	215	1 247	1 247
Females							
ATT	-0.058	-0.116	-0.110	0.001	0.031	-0.001	-0.036
	(-2.12)	(-2.62)	(-2.54)	(0.05)	(0.35)	(-0.14)	(-1.38)
ATE	-0.045	-0.126	-0.116	-0.006	0.019	-0.002	-0.037
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	√	√	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	X	√	√	√	X	√	√
B	√	√	√	√	X	√	√
R	√	√	√	√	√	√	√
No. Obs	690	736	739	738	208	1 283	1 283
Matching algorithm C: Kernel							
Males							
ATT	-0.007	-0.004	-0.102	0.046	-0.005	0.027	0.003
	(-0.33)	(-0.10)	(-2.19)	(1.62)	(-0.07)	(2.26)	(0.13)
ATE	-0.007	-0.003	-0.097	0.050	-0.024	0.028	0.000
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	√	X	X	√	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	√	√	√
B	√	√	√	X	√	√	√
R	√	√	√	√	√	√	√
No. Obs	735	737	740	740	215	1 247	1 247
Females							
ATT	-0.056	-0.106	-0.102	-0.015	0.048	0.002	-0.025

	(-2.19)	(-2.41)	(-2.39)	(-0.53)	(0.61)	(0.24)	(-0.99)
ATE	-0.042	-0.116	-0.106	-0.020	0.032	0.000	-0.031
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	√	√	√	X	X	X	X
LR-test	√	√	√	√	√	√	√
Mean bias	√	√	√	√	√	√	√
B	√	√	√	√	√	√	√
R	√	√	√	√	√	√	√
No. Obs	690	736	739	738	208	1 283	1 283
Matching algorithm D: Local linear regressions							
Males							
ATT	-0.019	-0.026	-0.105	0.046	-0.002	0.027	-0.003
	(-0.70)	(-0.45)	(-1.72)	(1.37)	(-0.03)	(1.78)	(-0.10)
ATE	-0.016	-0.021	-0.098	0.047	-0.025	0.030	-0.005
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	X	X	X	X	X	X	X
LR-test	√	X	X	X	√	√	√
Mean bias	√	X	X	X	X	√	√
B	X	X	√	X	X	√	√
R	√	√	√	√	√	X	X
No. Obs	735	737	740	740	215	1 247	1 247
Females							
ATT	-0.068	-0.108	-0.106	-0.028	0.068	-0.000	-0.030
	(-2.19)	(-1.88)	(-1.88)	(-0.79)	(0.71)	(-0.04)	(-0.96)
ATE	-0.051	-0.117	-0.111	-0.026	0.052	0.000	-0.036
	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)	(n.r)
t-test	√	X	X	X	X	X	X
LR-test	X	X	X	√	√	√	√
Mean bias	X	X	X	X	X	√	√
B	X	X	X	√	X	√	√
R	√	√	√	√	√	√	√
No.Obs	690	736	739	738	208	1 283	1 283

Note: These are unweighted results. The T-statistics is reported in the parentheses and “n.r” denotes the t-statistics that STATA could not estimate. No. obs refers to the number of observations or sample size.

Strong financial protection is the end goal for every individual as it has the potential of increasing access to health care facilities and encouraging health seeking behaviour which lead to improved child health outcomes. The nearest neighbour matching algorithm in Table 7c, reports fever as statistically significant in both males and females with a reduction of 13.1% and 14.3% respectively. It is also important to note that wasting showed a reduction of 0.2%

on average treatment effects while showing and increase of 0.4% on ATT results in females. The calliper radius matching algorithm is sufficiently balanced for all outcome models except vitamin A deficiency in both females and males which has an overall bias that is greater than 25. Anaemia, coughing and fever are statistically significant for females with a reduction in their prevalence of approximately 5.8%, 11.6%, and 11% respectively. Only fever is statistically significant for males, and strong financial protection reduces it by 11.1%. Other female outcomes that were reduced by strong financial protection include wasting and stunting.

The kernel matching algorithm has high quality of matching and is sufficiently balanced for all outcome models in females as they met Rubin's R and B statistical conditions meanwhile diarrhoea's outcome model was not sufficiently balanced as it did not meet Rubin's B condition in males. Anaemia, coughing and fever are statistically significant and are reduced by strong financial protection for females and fever having the only statistically significant average treatment effect on the treated result for males. The local linear regression algorithm reports that anaemia's average treatment effect on the treated is statically significant for females with a reduction of 6.8%. The male ATE and ATT effects show a reduction in anaemia, coughing, fever, vitamin A deficiency and stunting whilst the female ATE and ATT effects show a reduction in coughing, fever, diarrhoea, wasting and stunting but are statistically insignificant. Strong financial protection increases the prevalence of wasting as per the ATT results for males and in contrast a reduction in females.

5. Discussion

Gupta *et al.*, (2021) acknowledge that children born in low-income households and end up receiving some components of nurturing care which includes good health are at the advantage of developing to their greatest potential. For children to exhibit good health, they have to be financially protected and be able to access health care services which will improve their health. Financial protection is therefore important in young children as it enables them to invest in their health stock from a young age. The objective of this study is to estimate the financial protection's treatment effects when proxied by health insurance, affordability, and strong financial protection on child health outcomes. It is important to note that the analysis assumes that selection into treatment is based on observable characteristics described in the methodology and descriptive statistics sections.

The treatment effects on the treated and average treatment effects confirm that fever and coughing which were statistically significant in most instances. This finding corresponds with the hypothesis that financial protection is likely to reduce morbidity and mortality due to the childhood illnesses. The study showed that in some instances (i.e. where there was weak balance), treatment may have unintended consequences like increasing the prevalence of childhood illnesses instead of reducing them. This may be a result of poor balancing of the outcome models, poorly specified treatment models and small sample sizes for some outcome models like vitamin A deficiency (Caliendo & Kopeinig, 2008). Calliper radius matching algorithm outcome models were sufficiently balanced when treatment was affordability and strong financial protection. For these matching algorithms all outcome models met most, if not all of the quality of matching criteria.

The results of calliper radius matching algorithm indicate that being able to afford the cost of necessary healthcare services increased the prevalence of vitamin A deficiency and wasting. Similarly, strong financial protection increased the prevalence of diarrhoea, vitamin A deficiency and wasting. This may imply that households that can afford necessary health care services and have strong financial protection may not look after their health by taking risks with their health knowing that the costs associated with treatment will be borne by a third party like insurance or they have a contingency plan. Another factor to consider is that most people who are reliant on the public health care sector may report not finding it difficult to afford the costs of necessary health care as services like primary health care are free at public clinics and hospitals therefore, they may also display moral hazard. Moral hazard for these individuals is more likely to occur by neglecting their health, taking health risks knowing that they have access to hospitals and do not have to incur costs directly. Where there is fear of moral hazard, gatekeeping can be used as a tool to reduce moral hazard and therefore treatment will not have unintended consequences like increasing some child health indicators.

Child health outcome models with treatment as health insurance were poorly balanced for all matching algorithms. The reason for this poor balance may be the sample sizes when treatment is investigated by sex or the number of observations in each matching algorithm which end up distorting the results and poorly specified treatment model. Caliendo and Kopeinig (2008) specify that when a full set of covariates is included in small samples, variance tends to be higher as some of the treated will be removed from the analysis or some units will have to be used multiple times. The SANHANES-1 descriptive statistics indicated that only 15% households reported to have health insurance and only 91 treatment observations were matched compared to 1290 observations in the control group. The lack of adequate treatment observations may have contributed to the poor balancing of the outcome models and low quality of matching. One of the ways Caliendo and Kopeinig (2008) suggest mitigating poor quality of matching and balancing of propensity score matching models, is to re-specify models until one gets balance, this option was done multiple times and there was failure to have a model that achieved balance for all the proxies of treatment. High order variables for age, income and education were perused and none of them provided sufficient balance for all treatment and outcome models. Caliendo and Kopeinig (2008) further suggest omitting variables to improve balance and matching quality. However, Heckman, Ichimura, and Todd (1997) argue that omitting important variables has the potential increasing bias in the treatment effects results. To support this argument, Rubin and Thomas (1996) state that variables can only be excluded from the analysis if it agreed that the variable is not related to the outcome.

The results also showed that treatment effects differ across sex. The differences were in terms of outcome models, whilst females saw a reduction in anaemia, coughing, fever, diarrhoea, wasting and stunting mostly, males saw a reduction in the prevalence of anaemia, coughing, fever, vitamin A deficiency and stunting only when treatment was strong financial protection. Moreover, even though males had a high prevalence in some outcome variables, like stunting and wasting, financial protection effects were statistically significant and stronger in females. These differences may be a result of genes, where females are quicker to respond to females than male children. These results necessitate eliminating minimal charges to make healthcare services affordable and strong financial protection for children in South Africa to improve both female and male child health outcomes. The benefits of having financial protection include but not limited to removing financial burden and providing financial protection to households in the lowest wealth index quintiles and the larger uninsured population. Financial protection enables protection against impoverishing medical costs or medical poverty and improve the economic well-being of households in the lowest wealth index quintile by freeing resources that were used for health purposes for spending on non-health activities (Wherry *et al.*, 2016).

Wasting, diarrhoea, vitamin A deficiency and anaemia outcome models did not in most cases support the hypothesis whilst stunting consistently showed a reduction in its prevalence, it was however statistically insignificant. Fever and cough on the other hand with good quality matching displayed statistically significant treatment effects on the treated. These results show that financial protection affects these childhood outcomes differently. The treatment effects are not the same in the outcome models. Most of the treatment models do not support the implementation of NHI in South Africa as health insurance as a proxy for treatment does not produce statistically significant results. However, to reduce the effects of coughing and fever, the results do support the hypothesis and would imply support the idea of universal health coverage where there are no minimal charges or user fees. The reason behind these mixed results may be that South Africa offers free primary health care services and the vast majority of the citizens are reliant on the public health care sector.

6. Limitations

The first limitation of this study is that children could not be matched to their mothers, however, using the household's unique number, their information could be matched to the household head's information. It is important to match children to their mothers because their views are thought to be a great support to children's progress, and they are an active part in children's lives. Secondly, the nearest neighbour and linear regression matching algorithms in all treatment and outcome models, rarely met all of the criteria for quality of matching. Health insurance as a proxy of financial treatment also follows the same path of poor results when it comes to quality of matching. Caliendo and Kopeinig (2008) suggest using the underlying index of the score estimation instead of using propensity scores for matching. This is advantageous because the index allows for differentiation between observations in the extremes of the distribution of the propensity score (Lechner, 2000a). The authors further suggest the "leave-one-out cross-validation where a set of variables to be used in propensity score are chosen by beginning with a minimal model containing only two variables.

Thirdly, the first proxy for treatment which is health insurance does not measure whether all children or an individual child is covered by health insurance or not. It explains, however, if their household head or someone else in the household has health insurance or not. This does not give a clear indication of whether a specific child is also covered by the health insurance, or the child was left off the health insurance because of affordability issues. This has the potential of giving biased and distorted results. For further research, collection of data that answers the question on children's coverage by health insurance is necessary. Vitamin A deficiency had a relatively low sample size and propensity score matching often requires large samples to improve common support and balance. Small samples usually experience a trade-off between bias and variance; therefore, the choice of matching algorithm is important (Caliendo & Kopeinig, 2008). The choice of matching algorithm depends in most instances, on the data structure. Using more than one neighbour may work since there are a lot of control group observations than treatment and this has the potential of improving the accuracy of estimates. Focus on treatment effects for one outcome model is recommended in terms of further research. Lastly, propensity score matches treatment and the control group only on observables, there could be unobservable characteristics that influences the quality of matching. Rosenbaum (2002) suggest using the bounding approach where it is determined whether treatment effects have been altered by unobservable variables and how strong theses unobservable variables influence the matching analysis.

7. Conclusion

This study used a propensity score matching analysis to investigate the treatment effects of financial protection for seven children health outcomes using the SANHANES 2011-2012 data. Three proxies for financial protection were used and four matching algorithms were applied. It was discovered that having strong financial protection and affordability resulted in improved fever and coughing child health outcomes in South Africa. In contrast, financial protection resulted in increases in the prevalence of anaemia, diarrhoea, vitamin A deficiency and wasting. Stunting showed insignificant reduction in its prevalence. The treatment effects on the treated vary across the sex of the child with females experiencing reductions in most of the health outcomes than males. This study provides mixed results on the average treatment effects on the treated and average treatment effects. There are a few possible explanations for these mixed results and firstly it may be due to free primary healthcare services offered in South Africa and secondly it may be a result of poor quality of matching of the treatment and outcome models and lastly it may be due to small sample sizes in some instances.

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