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Policies Addressing Barriers to Low-Income Women and Children's Health Care Utilization in the United States and Kenya: The Role of Physician Payments and Cash Transfer Programs

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Policies Addressing Barriers to Low-Income Women and Children's Health Care Utilization in the United States and Kenya: The Role of Physician Payments and Cash Transfer Programs

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

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List of abbreviations

ACA – Affordable Care Act
ACS – American Community Survey
BCG – Bacille Calmette-Guerin
CEAC – Cost-effectiveness acceptability curve
CHOICE - Choosing Interventions that are Cost-Effective project
CMS _ Center for Medicare and Medicaid Services
CPT - Current Procedural Terminology
CT-OVC – Cash transfer program for orphans and vulnerable children
DALYs – Disability Adjusted Life Years
DC – District of Columbia
DCS – Department of Children's Services
DPT – Diphtheria-Tetanus-Pertussis
DW – Disability weights
GDP – Gross Domestic Product
GEE – Generalized Estimating Equation
GLLAMM - Generalized linear latent and mixed model
ICD-9 – International Classification of Diseases, Ninth Revision
ICER – Incremental cost-effectiveness ratio
ITN - Insecticide treated nets
MAX– Medicaid Analytical eXtract
MOUD – Medication for Opioid Use Disorder
NAS – Neonatal abstinence syndrome
NH – Non-Hispanic
NSDUH – National Survey on Drug Use and Health
OLS – Ordinary Least Squares
OUD – Opioid use disorder
SUD – Substance abuse disorder
UNICEF – United Nations Children's Fund
WHO – World Health Organization
YLD - Years lived with disability
YLL – Years of life lost

Abstract

This dissertation examined two policies to improve low-income women and children's healthcare utilization: physician payments and cash transfer programs. Higher physician payments increase the supply of healthcare services while cash transfers increase individuals' demand for healthcare services. Cash transfer programs can improve health outcomes, yet the extent to which they are a cost-effective strategy is largely understudied. Therefore, this dissertation examines three overarching research questions:

1. Are Medicaid physician fees associated with access to substance abuse disorder (SUD) treatment among low-income women of reproductive age?
2. Do economic preferences moderate cash transfer program effects on children's health care utilization? Evidence from a randomized field experiment in Kenya.
3. Are cash transfer programs cost-effective in reducing infectious diseases amongst orphans and vulnerable children in Kenya?

Broadly, the evidence from these papers suggests that supply and demand driven public policies increase the use of healthcare services for low-income women and children. Specifically, higher state Medicaid physician payments improve access to SUD treatment for low-income non-Hispanic Black women of reproductive age. Further, cash transfer programs improve the use of preventative healthcare services for children, and this impact is moderated by a caregiver's time preference. Additionally, a cash transfer program is cost-effective in reducing illnesses amongst children compared to the status-quo. Policy makers should invest resources in policies supporting increased physician payments and cash transfers to improve low-income women and children's health.

Chapter I: Introduction

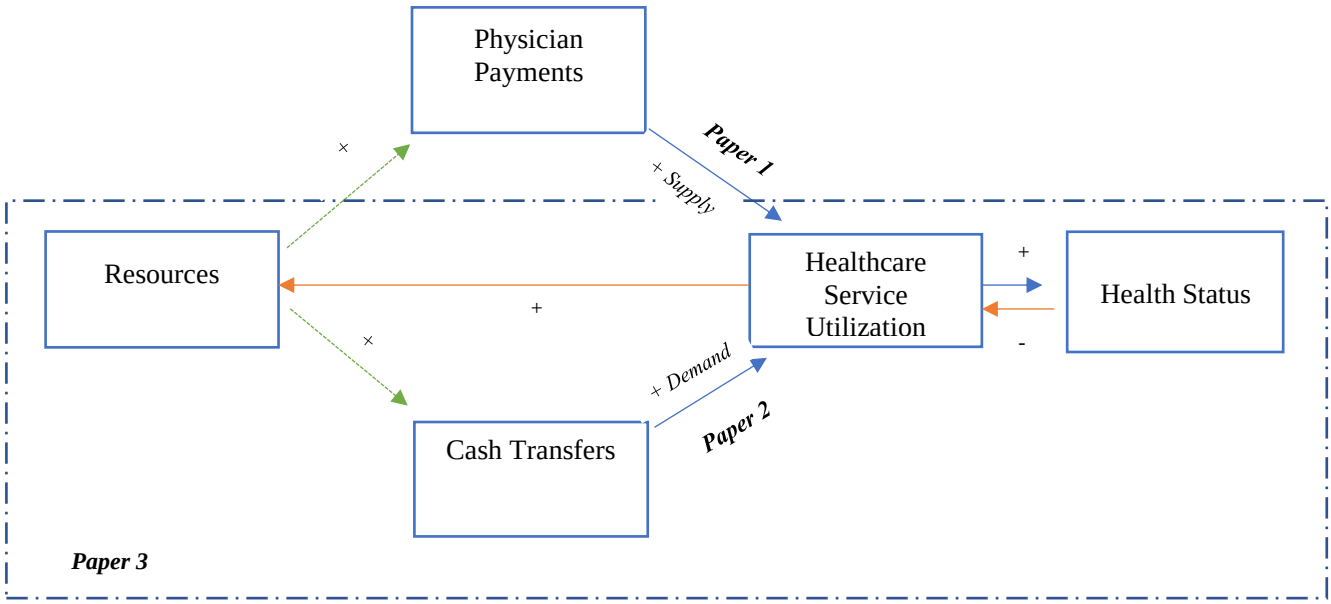
Approximately half of the people in the world are unable to access essential health services.[1] Inadequate use of healthcare services has contributed to poor health outcomes, especially among women and children. Policy makers have been working to increase healthcare services to low-income populations using supply-side policies that improve payments to health service providers who treat low-income populations[2] and/or demand-side policies that reduce the costs associated with accessing healthcare.[3]

In the United States, programs such as Medicaid provide public health insurance coverage to over 75 million low-income individuals.[4] With the passing of the Affordable Care Act (ACA) in 2014, a mandatory fee bump in Medicaid physician payments to align with higher Medicare payment rates was implemented to improve access to care for Medicaid enrollees.[2] While there is evidence that the fee bump to the supply-side improved access to care for low-income beneficiaries,[5] this fee bump was only mandatory for two-years and not all states have continued at the higher fee rates.[2] As states determine their own Medicaid reimbursement rates, the variation in Medicaid fee rates may have implications for the supply of quality healthcare for enrollees across the US. On the other hand, demand-side policies such as those implemented in sub-Saharan African countries, have reduced or eliminated out-of-pocket costs for essential health services.[6] Given that demand for healthcare is more price elastic among lower income populations, such policies aim to increase healthcare use.[6]

Nonetheless, significant supply- and demand-side barriers remain that limit the full potential of public sector delivery system reforms to improve the health of low-income populations.[6] This dissertation will conduct three studies to examine the effectiveness of two policies to address supply-and demand-side barriers to healthcare utilization: physician payments

and cash transfers. An overview of how the key concept across these studies relates is presented in Figure 1.

Figure 1: Overview of Dissertation Framework



About 25 million adult women are covered by Medicaid,[7] and their coverage includes a range of health services provided at low or no cost.[7] Regardless, these women face barriers in accessing care, such as limited access to providers, in part due to providers hesitance to accept Medicaid patients due to low Medicaid physician payments.[8,9] Given the importance of Medicaid for women's health, changes in the coverage, program's financing and structure have important implications for their access to care.[7]

The first paper of this dissertation explored the association of Medicaid physician payments (a supply-side policy) on healthcare utilization. With the continued increase in substance abuse

disorder (SUD) among women of reproductive age,[10] and the unmet need for treatment,[11] this paper specifically examines the association between Medicaid provider payments and substance abuse treatment. Leveraging the state-level variation in physician payments, the paper utilized Medicaid claims data (2008 -2012) to examine the association of Medicaid provider payments on access to SUD treatment.

In most developing countries, limited access to healthcare services is as a result of financial constraints preventing individuals from seeking necessary health care.[12] Cash transfer programs are demand-side policies that have been used to improve the well-being of low-income individuals and families by removing them from extreme poverty.[13] The increased household income works to remove or mitigate cost-related barriers to accessing healthcare use and result in increased demand.[14] Addressing the cost-related barriers to healthcare utilization, particularly for children, is expected to increase the prevention and treatment of diseases that have caused high mortality rates in developing countries.[14]

The second paper of this dissertation analyzed the extent to which cash transfers affect children's healthcare utilization. The paper is based on the premise that income shocks affect healthcare use for children and these effects are moderated by the economic preferences of caregivers (i.e., risk aversion and discount rates). The study used impact evaluation data from the Cash Transfer for Orphans and Vulnerable Children program (CT-OVC) implemented in Kenya. The additional income from the cash transfer program is expected to increase healthcare demand, however, levels of economic preferences held by caregivers receiving these payments are expected to moderate this effect.

In the third paper, the existing evidence that the CT-OVC program decreased infectious diseases (malaria and pneumonia) among children under seven years of age[15] is extended to assess

whether the program is a cost-effective strategy. The study conducted an incremental cost-effectiveness analysis to assess whether cash transfer programs, compared to the status-quo, are a cost-effective strategy in reducing infectious diseases amongst orphans and vulnerable children in Kenya. Assessing whether the program is cost-effective informs decisions by policy makers about which programs to fund, as there is an opportunity cost to other public programs associated with policies that expend limited resources on cash transfer programs.[16] Policy makers role in promoting appropriate healthcare use is essential, especially for low-income individuals who face many barriers in accessing care. This dissertation contributes to the literature on whether physician payments and cash transfer program can improve low-income women and children's healthcare utilization.

Chapter II: Are Medicaid physician fees associated with access to and quality of substance abuse treatment among low-income women of reproductive age?

2.1. Introduction

In the United States, approximately 90% of women with a substance use disorder (SUD), defined broadly as abuse or misuse of substances such as alcohol, opioids, heroin, cocaine and marijuana, are of reproductive age.[10] Despite a slight reduction in SUD amongst adults aged 18 years and older from 9.1% in 2008 to 8.8% in 2012,[17] there has been a continued increase in SUD amongst women of reproductive age. For instance, opioid use disorder (OUD) amongst pregnant women has been on the rise since the 1990s.[18,19] This increase in maternal opioid use has increased the incidence of neonatal abstinence syndrome (NAS) and results in substantially higher healthcare costs for hospital births and in the first years of life.[18,20–22] The risk of adverse birth outcomes such as fetal loss and preterm birth is also compounded in women with SUD.[19] Women of reproductive age also face unmet SUD treatment. A recent study found low receipt (9.3%) of SUD treatment amongst women of reproductive age who needed treatment.[23] There are a number of reasons for unmet treatment need, however treatment cost is a highly cited reason, such that low-income individuals may face significant barriers to treatment.[24] Additionally, people with disabilities, who have a high prevalence of SUD, face lower treatment rates.[25] Thus, low-income women of reproductive age and those with a disability are a key population at risk that require increased access to SUD treatment.[21]

Medicaid plays an important role in SUD treatment as 12% of its beneficiaries have a SUD[26] and it covers 40% of all US adults with OUD.[27] In 2017, only a third of individuals with an OUD covered by Medicaid received drug or alcohol treatment.[27] In a study of Medicaid enrollees, fewer than 47% of those with SUD who needed treatment received it.[28] In addition to the unmet

need for treatment for behavioral health outcomes,[11] there is also limited participation of behavioral healthcare providers in Medicaid.[29] Several studies suggest the low physician reimbursement rates, or fees, from Medicaid compared to other payers may hamper access to SUD treatment for beneficiaries.[8,9] Based on the economics literature, providers may be driven by the profit motive such that they will provide more services to other markets with higher payments and less administrative processes (Appendix A1 describes the theoretical framework for how low payments in Medicaid may affect the supply of services to its enrollees). Consequently, assessing the role of physician reimbursements in SUD treatment is crucial.

The role of Medicaid in SUD treatment for women of reproductive age intersects with other important populations who face significant barriers in health care access, such as racial and ethnic minorities. There are documented racial and ethnic disparities for SUD. Minorities face lower retention in SUD treatment,[30] and those with an opioid use disorder (OUD) specifically, are less likely to be treated compared to non-Hispanic (NH) Whites.[31] For instance, between 2008-2010, SUD treatment among people with past-year SUD, was estimated as 8% amongst NH-Whites, 3% amongst Hispanics, 7% amongst NH Blacks and 6% amongst NH-Asians.[32] In another study amongst adult outpatient visits in the US, NH-Blacks were treated less frequently than NH Whites.[33] Therefore, understanding the relationship between physician payments and access to SUD treatment for minorities is of importance in addressing racial and ethnic disparities.

Nonetheless, most studies have found a positive association of physician fees on various health outcomes and access to health services.[34–41] Higher Medicaid physician fees have been shown to increase the number of prenatal care visits and adequate prenatal care amongst pregnant women,[40] and reduce adverse birth outcomes such as preterm birth and low-birthweight.[39] These improvements in health outcomes are thought to result from increased provider payment rates

increasing access to care for Medicaid enrollees.[40] Similar findings have been documented among children, as there was an increase in take-up of insurance, preventive care visits, and having a usual source of care when provider payments increased.[37,42] Other studies have found increases in provider payments are associated with increases in the number of private physicians who see Medicaid patients and outpatient physician visits.[29,34]

However, only one study has examined the impact of Medicaid physician payment rates on SUD treatment.[29] This study found that higher Medicaid provider reimbursement rates improved behavioral health outcomes (any mental illness, SUD, and tobacco use) but had no effect on receipt of any SUD treatment.[29] This study was limited to survey data which may not accurately capture diagnosis or treatment of SUD due to self-reporting bias. In addition, this study primarily leveraged the Medicaid-fee bump, whose variation occurred over a short period of time which and may not reflect the differences in state policies.[29]

Therefore, utilizing Medicaid claims data and based on the variation in state-level physician reimbursement rates across 16 states, this study analyzed whether Medicaid physician fees are associated with access to SUD treatment among low-income women of reproductive age. We hypothesized that higher state Medicaid physician fees will be associated with increased access to SUD treatment (the conceptual framework for this paper is provided in Appendix AI). Considering the racial and ethnic disparities in SUD treatment,[23] we further examined whether this association varies by race and ethnicity to determine whether increased Medicaid payments can improve access to SUD treatment for minorities. We hypothesized that higher Medicaid physician fees will improve SUD treatments amongst minorities.

2.2. Methods

2.2.1. Data

The primary data source for this study is the 2008 - 2012 Medicaid Analytical eXtract (MAX) data.[43] This is a collection of enrolment and claims data from Medicaid agencies in each state. The federal government partners with states to manage and monitor the Medicaid program and converts the data collected into an aggregated standardized dataset. Our data contained information for Medicaid beneficiaries enrolled in a state through income and disability pathways. The Medicaid eligibility disability pathways include those with physical conditions (such as quadriplegia, traumatic brain injuries); intellectual or developmental disabilities (for example, cerebral palsy, autism, Down syndrome); and serious behavioral disorders or mental illness (such as schizophrenia or bipolar disorder).[44] We used two files of the MAX data, the MAX Other Service (OT) file and the MAX Personal Summary (PS). The MAX OT includes claims records for the different Medicaid services received,[45] while the MAX PS file contains a record for an individual eligible and enrolled in Medicaid for a minimum of one month or had a service paid for by Medicaid in a year.[46] This dataset was additionally ideal for our analysis as it provided geographical identifiers to merge with state and county level characteristics obtained from other data sources.

Additional data was obtained from the Kaiser Family Foundation,[47] the American Community Survey[48,49] and the National Survey on Drug Use and Health (NSDUH)[50]. The Urban Institute collects data on physician fee ratios using a survey conducted every two years collecting data from providers. The Medicaid-to-Medicare fee ratio is obtained from the Urban Institute to proxy Medicaid physician payments. The American Community Survey (ACS) provide state and

county-level characteristics. We include county-level income, education, employment, and urbanicity from the ACS. The NSDUH provides annual estimates of SUD prevalence in each state.

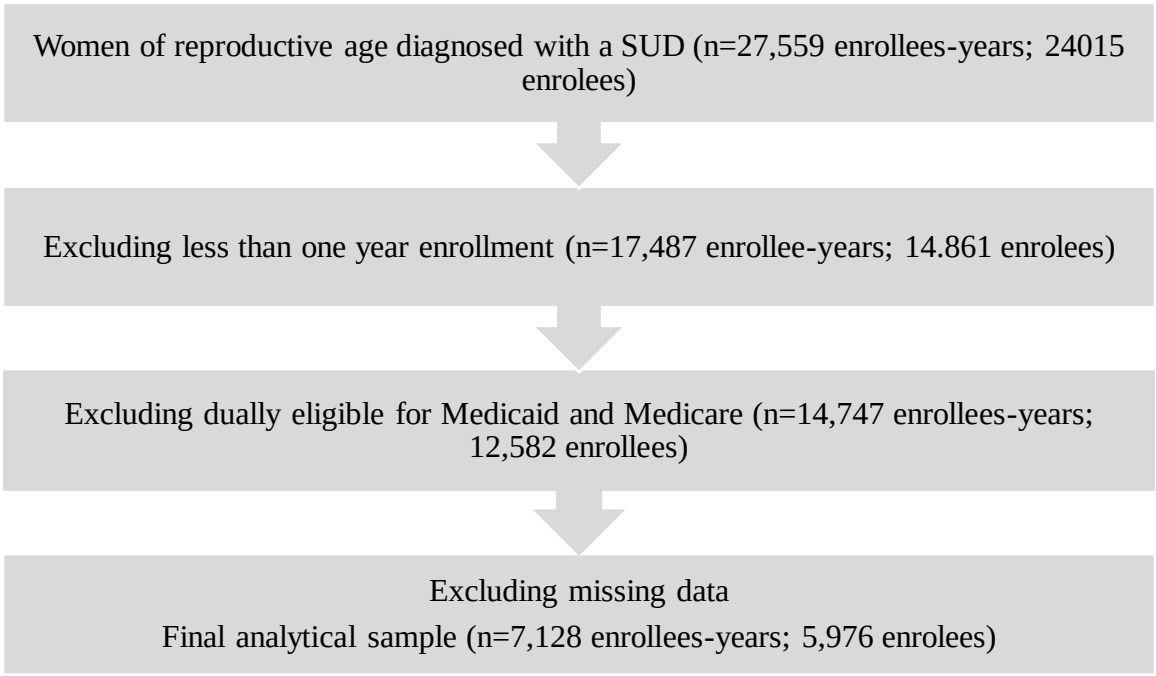
2.2.2. Sample

Data completeness and quality of the claims data was assessed with state-years not meeting data user checks in the MAX OT file. The sample included women of reproductive age (18 – 50 years)[51] enrolled in Medicaid through the disability and income pathways and had been diagnosed with SUD based on ICD9 codes to identify SUD [n=27,559 enrollee-years; Appendix AII provides ICD-9 codes)]. The sample included Medicaid patients in the following states: Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Kentucky, Mississippi, Louisiana, Oklahoma and Texas. These states in the selected regions have varying SUD prevalence. For instance, West Virginia has the highest age-adjusted rate of drug overdose (52%) in the country, while the District of Columbia (DC) has the highest SUD prevalence (12% for adults aged 18 and older).[52] There is also variation in SUD treatment need. DC has the highest unmet SUD treatment need while North Carolina has the lowest. [52] This analysis considered states near these states for comparability but also offered variation in SUD prevalence and treatment needs.

The sample included women with continuous enrollment for one calendar year (n=17,487 enrollee-years). The sample excluded those dually eligible for Medicaid and Medicare (n=2,740 enrollee-years).[53] As this study examined treatment utilization under Medicaid, health service utilization under Medicare claims could not be examined in the MAX data and therefore would not be a complete record of service utilization. We excluded data with missing county level

characteristics (n=7,619 enrollee-years). The final analytical sample comprised 7,128 enrollee-years.

Figure 2: Data flow-chart diagram



2.2.3. Access to SUD treatment

Access to SUD treatment is the dependent variable defined as the receipt of any SUD treatment following a diagnosis of any SUD within a calendar year.[54,55] We include SUD treatment in the analysis as a binary measure for receipt of any SUD treatment within a calendar year. Appendix AIII provides the CPT-codes used to define SUD treatment.

2.2.4. Medicaid Physician Fees

The primary independent variable is the Medicaid-to-Medicare fee ratio which represents the level of Medicaid fees in a state relative to the Medicare level. The Medicaid-to-Medicare fee ratio serves as a proxy for the level of Medicaid physician fees in each state. The Medicaid-to-Medicare fee ratio is appropriate as the ratio varies by state (Table 1). As treatment of SUD is increasingly being delivered in primary care settings, for instance Medication for Opioid Use Disorder (MOUD),[29] the primary care fee ratios work as the best proxy from the other two types of fee ratios currently available (pediatrics and gynecology). The Medicaid physician surveys collected by the Urban Institute were only conducted in 2008 and 2012 during the observation period of this study. Following prior previous literature,[29,35] we use a linear model to interpolate the fees for each state for the years these ratios are unavailable. The Medicaid-to-Medicare fee ratio is assessed as a continuous variable in the analysis.

2.2.5. Covariates

We control for variables identified in the literature as associated with SUD treatment[29,34,35,56] and based on Andersen's behavioral model (Appendix AI provides the conceptual model).[57] Predisposing characteristics included the age, and race and ethnicity. Age of a patient at time of diagnosis was measured as a categorical variable (<25 years, 25-34 years, 21-44 years, and 45+ years) while race and ethnicity were measured as a categorical variable (non-Hispanic (NH) White, NH Black, Hispanic and other). Enabling factors included income, education, employment, and urbanicity. In the absence of individual-level characteristics, we included these as country-level factors.[29,41] Income is included as a continuous variable measuring the average household income in the county. We log-transformed the income variable to

approximate a normal distribution. Education is measured as a continuous variable measuring the share of the population in a county with more than a high school education and employment is the share of the population in the county employed. Urbanicity was defined as the share of the population living in an urban area (or in a metropolitan area). County-level education, employment and urbanicity, as well as the state-level SUD variable, were divided by 10 to represent the effect of a 10-percentage point change of these variables on access to SUD treatment in our regression models. Need factors included the state SUD prevalence measured as a continuous measure and a binary measure for whether an individual had a comorbidity. A comorbidity was defined as having any other diagnosis besides an SUD diagnosis. Additionally, we included a binary measure for whether an individual was enrolled in managed care plan. We also controlled for state and year fixed effects to account for unobservable state- and year-specific time invariant characteristics that may affect access to SUD treatment.

2.2.6. Statistical analysis

The study analysis was based on the variation in Medicaid physician fees across states and over time. To estimate the association of Medicaid physician fees on the access to SUD treatment, we estimate the following linear probability model:

$$Y_{ist} = \beta_0 + \beta_1 Fee_{st} + XB + \varsigma_{st} + \lambda_t + State + Year + \varepsilon_{ist} \qquad \text{(i)}$$

The dependent variable *Y* for individual *i* in state *s* and year *t* was analyzed as a function of Medicaid-to-Medicare fee ratio in state *s* and year *t*, controlling for individual *X*, county ς and State λ characteristics are as described above. We divided the fee ratio by 10 for our regression

models for ease of interpretation of the β_1 coefficient. For instance, if the ratio is 0.85 and increases by 1 unit, that would be an increase to 1.85, which is an increase of 100-percentage points. Therefore, dividing by 10 would make a unit increase as a 10-percentage point change. The estimate β_1 therefore represents the probability of an enrollee receiving SUD treatment given a 10-percentage point increase in the Medicaid-to-Medicare fee ratio. The *State* and *Year* is included to control for unobserved factors that are time-invariant factors across state and year, respectively.

To assess whether Medicaid reimbursement policies can improve access to SUD treatment for minorities (NH-Blacks), we run stratified models by race and ethnicity. We additionally run a parameter stability to estimate the unrestricted and restricted model to test whether the parameters are different by race and ethnicity. The unrestricted model included two separate models for NH-white and NH-Blacks as follows:

$$Y_{ist} = \beta_0 + \beta_1 Fee_{ist} + XB + \varsigma_{st} + \lambda_t + State + Year + \varepsilon_{ist}, \text{ i=1,2…, N} \quad \text{(ii)}$$

$$Y_{jst} = \alpha_0 + \alpha_1 Fee_{jst} + X\alpha + \varsigma_{st} + \lambda_t + State + Year + \varepsilon_{jst}, \text{j=1,2…,M} \quad \text{(iii)}$$

The parameter stability null hypothesis that was tested across race and ethnicity was Ho: $\beta_0=\alpha_0$ $\beta_1=\alpha_1$, $\beta=\alpha$. The restricted model was as in model i, where i=1,2,..(N+M). The f-statistic was computed to test the null hypothesis using the followingmequation:

$$F\ statistic = \frac{\frac{SSR_r - (SSR_1 + SSR_2)}{2}}{\frac{(SSR_1 + SSR_2)}{(N + M - 4)}}$$

Where SSR represents the residue sum of squares, SSR_r is the SSR from our restricted model and $SSR_1 + SSR_2$ is the total SSR from equation (ii) and (iii) above. A significance level of $p<0.05$ was used for all analysis. All analyses were conducted in SAS.

2.2.7. Sensitivity analysis

Firstly, as we created linear estimates for the fee ratio in the years where they are unavailable, we conducted a sensitivity analysis using only the 2008 and 2012 data where the fee estimates are available. We conducted this sensitivity analysis to assess whether there are any differences in the estimates when we compare the results to those from the models using the linear estimates of the fee ratio for 2009-2011. Secondly, we examined an additional model to assess differences in SUD treatment by race and ethnicity when the fee ratio increases. As we observed the racial and ethnic disparities in SUD treatment, we run this sensitivity analysis to assess whether the effect of the fee ratio on SUD treatment is larger, smaller or the same depending on minority status. We run the following model:

$$Y_{ist} = \beta_0 + \beta_1 Fee_{st} + \beta_2 M_{st} + \beta_3 Fee * M_{st} + XB + \varsigma_{st} + \lambda_t + State + Year + \varepsilon_{ist}$$

(iv)

The variable M_{st} is a binary measure equal to 1 if the Medicaid enrollee is a NH-Black woman. β_3 represents the change in probability of an enrollee receiving SUD treatment by minority status given a 10-percentage point increase in the Medicaid-to-Medicare fee ratio. A significant positive β_3 would suggest that an increase in the fee ratio has a larger effect for minorities, while significant negative β_3 would suggest that the effect is larger amongst NH-Whites.

Thirdly, we examined the association of the fee ratio and receipt of any SUD treatment restricted to individuals who were enrolled in managed care only.

2.3. Results

Table 1 provides the Medicaid-to-Medicare fee ratio across 16 states included in this study. The ratio represents the level of Medicaid fees in a state relative to the Medicare level. For instance, in 2008, the Medicaid fee level in Arkansas was 23% less than the Medicare level while North Carolina's Medicaid fee level was 5% less than the Medicare level. Oklahoma, on the other hand, had Medicaid fees that were the same as the Medicare level in 2008. The Medicaid-to-Medicare fee ratios vary across these states with Delaware having the highest fee ratio in both 2008 and 2012. In 2008, the District of Columbia had the lowest fee ratio and in 2012 Florida had the lowest.

Table 1: Medicaid-to-Medicare fee ratio

State	2008	2009	2010	2011	2012
United States	0.65	0.63	0.62	0.60	0.58
Alabama	0.77	0.75	0.73	0.70	0.68
Arkansas	0.77	0.75	0.73	0.70	0.68
Delaware	1.00	1.00	0.99	0.99	0.98
District of Columbia	0.45	0.54	0.63	0.71	0.80
Florida	0.55	0.54	0.52	0.51	0.49
Georgia	0.86	0.81	0.77	0.72	0.67
Kentucky	0.79	0.77	0.75	0.72	0.70
Louisiana	0.90	0.86	0.83	0.79	0.75
Maryland	0.82	0.79	0.76	0.72	0.69
Mississippi	0.83	0.85	0.87	0.88	0.90
North Carolina	0.95	0.93	0.90	0.88	0.85
Oklahoma	1.00	0.99	0.99	0.98	0.97
South Carolina	0.86	0.83	0.80	0.77	0.74
Texas	0.69	0.67	0.65	0.62	0.60
Virginia	0.88	0.85	0.81	0.78	0.74
West Virginia	0.76	0.76	0.75	0.75	0.74

Source: 2008 and 2012 values from the Kaiser Family Foundation[47] while 2009-2011 were interpolated using linear estimates

Table 2 provides the summary characteristics of the sample. Enrollees mainly had alcohol use disorder in 54% of their enrollee years followed by an opioid use disorder with 24% of their enrollee years. Hallucinogens was the least abused substance in their enrollee-years. Approximately 27% of women diagnosed with a SUD received any treatment for SUD in their enrollee-years. The sample comprised 49% white women mainly aged 35-44 years (37%). Additionally, there are racial and ethnic disparities in SUD treatment: 24.12% of NH Whites received SUD treatment, compared to 15.86% ($p<0.05$) of NH-Blacks and 34.01% ($p<0.05$) amongst Hispanics.

Table 2: Sample characteristics, 2008-2012

Variable	Full sample (N=7,128 enrollee-years) n	%
SUD diagnosis:		
Alcohol	3822	53.6
Cannabis	121	1.7
Cocaine	291	4.1
Drug-induced mental disorder	847	11.9
Hallucinogens	109	1.5
Other	236	3.3
Opioids	1702	23.9
Received any SUD treatment	1934	27.1
Medicaid-to-Medicare fee ratio*	0.76	0.14
Age[#]:		
<25 years	882	14.8
25-34 years	1403	23.5
35-44 years	2237	37.4
45+	1454	24.3
Race and ethnicity[#]:		
NH-White	2937	49.1
NH-Black	2216	37.1
Hispanic	500	8.4
Other	323	5.4
County characteristics*:		
share of population with more than high school education	0.68	0.06
share of population living in an urban area	0.73	0.38
share of the population employed	0.58	0.06
average household income (ln($))	12.86	0.46
Comorbidity	3312	14.5
Managed care	6661	93.5
State SUD prevalence (%)*	22.14	1.79
State of enrollment:		
Alabama	68	0.9
Arkansas	126	1.8
District of Columbia	553	7.8
Delaware	890	12.5
Florida	418	5.9
Georgia	205	2.9
Kentucky	220	3.1
Louisiana	1892	26.5

Maryland	87	1.2
Mississippi	934	13.1
North Carolina	34	0.5
Oklahoma	43	0.6
South Carolina	1383	19.4
Texas	275	3.9
Virginia	68	0.9
Year of enrollment:		
2008	3361	47.2
2009	677	9.5
2010	818	11.5
2011	1017	14.3
2012	1255	17.6

* Showing means and standard deviation; # reporting at the enrollee level

2.3.1. The association of Medicaid fees and SUD treatment

Table 3 provides the association of the Medicaid-to-Medicare fee ratio and access to SUD treatment. We do not find a significant association of the fee ratio and receipt of any SUD treatment. However, we find that the probability of receiving SUD increased with age. Specifically, compared to women aged less than 25 years, those aged, 25-34 years, 35-44 years and more than 45 years were more likely to receive SUD treatment [β=0.11($p<0.01$), β=0.15 ($p<0.01$), and β=0.18 ($p<0.01$), respectively]. Compared to white women, NH-black women were less likely (β=-0.06, $p<0.01$) to receive SUD treatment while Hispanic women were more likely (β=0.04, $p<0.01$) to receive SUD treatment. In addition, higher education was associated with higher receipt of SUD treatment (β=0.004, $p<0.01$), while those that lived in an area with a high population of employed individuals was associated with lower probability of receipt of SUD treatment (β=-3.28, $p<0.01$). A woman in a state with a higher SUD prevalence had a higher probability of receiving SUD treatment.

Table 3: Regression results for receipt of any SUD treatment

	Full sample (N=7128 enrollee-years)	
	β	**Standard error**
Medicaid-to-Medicare fee ratio	0.027	0.02476
Age (ref: <25 years):		
25-34	0.105***	0.01699
35-44 years	0.154***	0.01571
45+ years	0.184***	0.01691
Race and ethnicity (ref: NH-White):		
NH-Black	-0.059***	0.01160
Hispanic	0.040**	0.02051
Other	-0.031	0.02127
Share of the population employed, county	-3.28***	1.18324
Share of the population with more than high school, county	0.004***	0.00150
Share of the population living in an urban area, county	-0.171	0.15519
Average household income (ln($)), county	-0.013	0.01546
Comorbidity	-0.002	0.01016
Managed care	0.027	0.02545
SUD prevalence (%)	-0.20***	0.02314
State (ref West Virginia):		
Arkansas	-0.609***	0.10837
District of Columbia	1.111***	0.10846
Delaware	0.441***	0.07275
Florida	0.097	0.07722
Georgia	-0.009	0.04193
Kentucky	-1.045***	0.14707
Louisiana	-0.249***	0.06019
Maryland	-0.821***	0.13755
Mississippi	-0.164***	0.05311
North Carolina	-0.469***	0.10505
Oklahoma	-0.302***	0.09088
South Carolina	-0.176***	0.07860
Texas	-0.609***	0.10837
Virginia	1.111***	0.10846
Year (ref: 2012):		
2008	0.029**	0.00754
2009	0.111	0.11289
2010	0.312	0.28863
2011	0.242	0.23362
Intercept	-55.55***	15.48

*** p<0.01; ** p<0.05; *p<0.1; reporting liner probability estimates; Alabama and West Virginia missing since they are. a linear combination of other variables in the model

2.3.2. The association of Medicaid fees and SUD treatment by race and ethnicity

Table 4 provides the results of the association of Medicaid fees and SUD treatment stratified by race and ethnicity. We find that amongst NH-Black women with a SUD diagnosis enrolled in Medicaid, a 10-percentage point increase in the Medicaid-to-Medicare fee ratio was associated with an 8% (p<0.01) higher probability of receiving any SUD treatment. Amongst both NH-Whites and NH-Blacks, we find that there is a lower probability of receiving SUD amongst younger women. For instance, compared to women aged more less than 25 years, those aged more than 45 years were more likely to receive SUD treatment [β=0.17 (p<0.01) amongst NH-Whites and β=0.13 (p<0.01) amongst NH-Blacks. We find a lower probability. (β=-0.41, p<0.01) of a NH-White women in an urban area receiving SUD treatment. Finally, both NH-White and NH-Black women in states with a higher SUD prevalence were less likely to receive any SUD treatment.

The results of the parameter stability found an F-statistic of 766 as shown below:

$$F\ statistic = \frac{\frac{1183 - (638 + 307)}{2}}{\frac{(638 + 307)}{(3585 + 2479 - 4)}} = 766$$

This represents a p-value of 0.000, and we can reject the null that the estimates from the stratified regression models are the equal. Therefore, the specification of the stratified models is appropriate.

Table 4: Regression results for receipt of any SUD treatment, by race and ethnicity

	NH-Whites (n=4055)		NH-Black (n=2819)	
	β	Standard error	β	Standard error
Medicaid-to-Medicare fee ratio	-0.025	0.04123	**0.08*** **	**0.03067**
Age (ref: <25 years)				
25-34	0.11***	0.02296	0.081***	0.02809
34-44	0.13***	0.02200	0.128***	0.02535
45+ years	0.17***	0.02435	0.134***	0.02691
Share of the population employed, county	-2.62*	1.57254	-0.854	2.34015
Share of the population with more than high school, county	0.003	0.00230	0.002	0.00337
Share of the population living in an urban area, county	-0.41**	0.20931	0.118	0.28149
Comorbidity	-0.022	0.01486	-0.019	0.01494
Average household income (ln ($)), county	0.013	0.02038	-0.025	0.02943
Managed care	0.049	0.03579	-0.012	0.03601
SUD prevalence (%)	-0.26**	0.03376	-0.14***	0.03158
State (ref West Virginia):				
Arkansas	-0.87***	0.15680	-0.33**	0.14908
District of Columbia	1.044***	0.23093	0.856***	0.14990
Delaware	0.645***	0.11594	0.267**	0.09636
Florida	-0.0412	0.12470	0.235**	0.10119
Georgia	-0.091	0.06273	0.067	0.05577
Kentucky	-1.42***	0.21434	-0.73***	0.20135
Louisiana	-0.35***	0.08618	-0.683**	0.19792
Maryland	-	-	-0.093	0.07202
Mississippi	-1.11***	0.19489	-0.62***	0.17118
North Carolina	-0.21***	0.07713	-0.085	0.13435
Oklahoma	-0.47***	0.14929	-0.04***	0.11038
South Carolina	-0.44***	0.12853	-0.683	0.19792
Texas	-0.35***	0.11990	-	-
Year (ref: 2012):				
2008	-0.52***	0.1215	0.057***	0.0102
2009	0.22	0.1263	0.002	0.1763
2010	0.26**	0.1157	0.24	0.1823
2011	0.24**	0.1222	0.09	0.1814
Intercept	-39.9	944.0	-113***	21.922

*** p<0.01; ** p<0.05; *p<0.1; reporting liner probability estimates; some states are missing since they are a linear combination of other variables in the model

2.3.3. Sensitivity analyses

In the analysis of the association of the Medicaid-to-Medicare fee ratio and SUD treatment using only the 2008 and 2012 data (Appendix A4.1), we find a 15% ($p<0.01$) higher probability of receiving SUD treatment associated with a 10-percentage point increase in fee ratio amongst NH-Black women. These findings are in line with the estimates from the main regression model. However, when we run a model including an interaction term (Appendix A4.2), we find a significant difference ($\beta=0.22$, $p<0.01$) in the effect of an increase in Medicaid physician fees and SUD treatment by minority status. This means that increases in the state Medicaid-to-Medicare fee ratio affect SUD treatment amongst women, and this differs by race and ethnicity when we compare NH-Black women to NH-White women. The finding from the interaction model supports our main findings from the stratified model as we found a significant effect amongst the NH-Black sample and no effect in NH-White sample. Finally, our findings are robust to restricting the sample to only those enrolled in managed care as we find an 8% increase in the probability of receiving SUD treatment amongst NH-Black women when the fee ratio increases by 10-percentage points. (Appendix A4.3)

2.4. Discussion

This study analyzed the association of Medicaid physician fees with access to SUD treatment among women of reproductive age in 16 states in the United States. Noting the racial and ethnic disparities in SUD treatment, where NH-Whites are more likely to receive SUD treatment compared to NH-Blacks we additionally examine whether increasing Medicaid physician fees can address the racial and ethnic disparities in treatment. We find that among NH-Black women, higher Medicaid fees increase the likelihood of receiving SUD treatment. These findings contribute to the literature on physician payments and access to SUD treatment by being

the first to analyze this association amongst a key population (low-income women of reproductive age living with a disability) that face huge obstacles in access to SUD treatment in the US.

Similar to a prior study,[29] we did not find an association of Medicaid fees and SUD treatment when we examined this association amongst the full sample that included all race and ethnicities. However, when we stratify the sample by race and ethnicity, we find that higher state physician payments increase the likelihood of NH-Black women of reproductive age receiving SUD treatment, and this differs from the findings of the study.[29] In addition to the stratification by race and ethnicity, this difference could be explained by the difference in sample as our study focused on low-income women of reproductive age with a disability compared to the prior study that examined the general population. Our findings show that the lower fees for Medicaid providers compared to other providers may be a barrier to accessing SUD treatment for minorities. As NH-Black women face more barriers to accessing SUD treatment, we show that even a modest improvement in public service delivery will increase access for the more vulnerable populations.

We find that younger women are less likely to receive SUD treatment. Specifically, women aged more than 45 years were more likely to access SUD treatment compared to those aged less than 25 years, 25-34 years, or 35-44 years. The finding that use of health services differs by age is contrary to other literature showing that access to care increases with age.[34] Similarly, our findings on SUD treatment and women in areas of higher education status and urbanicity are not aligned to prior literature. These differences could be explained by the differences in the sample composition of this study. Further, there is no study to our knowledge that has examined access to SUD treatment amongst a low-income Medicaid population.

2.4.1. Limitations

This study has several important limitations. Firstly, the data on the Medicaid-to-Medicare ratios are only available for the years 2008 and 2012. To address this limitation, we use linear models to estimate the fee ratios for the missing years (2009-2011). However, our main findings are robust to replicating our analysis using only the 2008 and 2012 data. Secondly, the study findings may not be applicable to the general population as our study sample includes women of reproductive age who were eligible for Medicaid under disability and income. However, this study is the first to our knowledge providing evidence on the association of Medicaid physician fees and SUD treatment among a key population of interest. The study sample includes women who were eligible for Medicaid under disability and income. Low-income individual's generally have less access to healthcare services, and people living with disability (PWD) are a vulnerable population that experience additional barriers to SUD treatment. Therefore, this sample selection likely underestimates the number of individuals who receive treatment, and this makes our estimates conservative. Our findings suggest that this key population may receive higher SUD treatment if physician payments in their states increased.

Additionally, as with many diagnosis using claims data, there might be misdiagnosis related to having an SUD. Although we do not address this limitation, we anticipate that this limitation underestimates the treatment effect as those with more SUD diagnosis have more interaction with the healthcare system and would be more likely to receive SUD treatment. Therefore, our estimates are conservative, and we do not anticipate that this would affect our policy conclusion that higher state Medicaid fees can improve access to SUD treatment. We also note that our findings could be sensitive to the ICD-9 or CPT codes used in our analysis. However, we reviewed the literature on diagnosing and treating SUDs and used those codes mainly reported in

the peer review literature. We additionally cross-referenced the codes with those provided by the CMS. Similarly, our findings may be sensitive to the fee ratio used in our analysis as there are various fee estimates published. However, we do not anticipate that this will affect our policy conclusions as the differences in the ratios are only slight.

Finally, this study does not provide evidence on the causality of Medicaid physician fees and SUD treatment for women of reproductive age and should be interpreted with caution. Assessing causality requires examining the effect of an exogenous policy change, such as the ACA Medicaid fee bump in 2014. Although we are unable to assess the impact of this change due to the period of data availability, this study provides initial evidence on the relationship between state Medicaid physician fees and access to SUD treatment amongst a key population of interest. Future studies could extend this analysis to a larger population (e.g., the entire Medicaid population), additional outcomes (e.g., regular receipt or the quality of SUD treatment), and other vulnerable populations (e.g., people living with HIV).

2.4.2. Conclusion

Limited provider participation in the Medicaid market, in part due lower fees compared to other payers, has been an ongoing concern for policy makers as this affects access to care for Medicaid enrollees.[29] While there have been efforts to improve provider payments, such as the 2014 Medicaid fee bump, to improve access to care for beneficiaries, significant state variation in Medicaid payment rates still exist.[2,5] This study analyzed whether there is an association of Medicaid state fee rates and access to SUD treatment among women of reproductive age. Given the importance of Medicaid for women's health,[7] changes in Medicaid reimbursement policy can have important implications for their access to care. Our findings are important for Medicaid policy

as we show that increases in reimbursement rates for providers improves SUD treatment outcomes for low-income women. Specifically, we provide evidence that higher physician payments can be used as tool to address the unmet treatment need of minorities, especially among NH-Black women. Our study supports intervention in Medicaid reimbursement policy, as Medicaid disproportionately pay for services for SUD treatment and for women of reproductive age. Without changes to the Medicaid fee rates, the incidence of SUD among women may continue to rise leading to even higher healthcare utilization and costs in the US.

Chapter III: Do economic preferences moderate cash transfer program effects on children's health care utilization? Evidence from a randomized field experiment in Kenya

3.1. Introduction

In Kenya, under-five mortality is high with approximately 41 deaths per 1000 live births.[58] The leading causes of these deaths include malaria, pneumonia and diarrhea which are preventable and treatable.[59,60] The World Health Organization (WHO) recommends regular use of healthcare services to address treatable and preventable illnesses that cause the high mortality rates.[61] However, parents or caregivers face numerous barriers, such as financial constraints, that limit access to healthcare services for their children.[12] Low income is a well-established risk factor associated with inadequate access to healthcare for children, leading to poor health, and increased under-five mortality.[62–64] In developing countries where the majority of the people are poor, caregivers may not be able to afford transportation to access care or pay out-of-pocket costs once they get there, and the time cost of substituting work hours for healthcare visits is high.[64] Cash transfer programs are a common strategy in developing countries to lift low-income individuals out of poverty such that the aforementioned barriers can be addressed, and child healthcare utilization can improve.[14]

In 2007, Kenya's largest social protection program, the Cash Transfer for Orphans and Vulnerable Children (CT-OVC) program was rolled out as a pilot by the Ministry of Gender, Children and Social Development.[65] This cash transfer program was implemented in Kenya to promote human capital development through improving children's health.[66] Specifically, it aims to reduce under-five morbidity and mortality, particularly through increasing immunization rates, growth monitoring and uptake of vitamin A supplements.[66] Immunization is crucial to prevent life-threatening illnesses in children, such as polio, measles and tuberculosis.[67,68] Growth monitoring

is a preventative measure involving routine measurement of the weight or height of a child to judge the physical conditions of child and provide the appropriate care when abnormalities are detected.[69] Vitamin A supplements are crucial for children's growth, and a deficiency leads to night blindness and increases the risk of illnesses and death.[70] However, while the aim of the CT-OVC was to improve children's health and wellbeing, there were no conditions attached to receiving the cash transfer. The CT-OVC pilot disbursed approximately $10 million dollars to households in seven districts.[66] The program has since been scaled up, and has been incorporated in the governments annual national budget.[71]

Prior evaluations of the CT-OVC program find mixed evidence on the effect of healthcare utilization. For instance, one study found no effect on seeking diarrhea treatment for children under the age of seven years,[15] while another found the program increased consulting an appropriate source of care when there was an illness.[66] One limitation of prior evaluations of the CT-OVC program was the limited length of follow-up observations (two years) on children's health and health care use.[15]

Several other cash transfer programs have been implemented in developing countries, and similarly, there is mixed evidence on their effect on healthcare utilization.[13,72–76] An evaluation of an unconditional cash transfer program implemented in Zambia found very limited evidence of a positive impact on children's curative or preventive health service utilization.[74,75] Although, a 24 month evaluation of Zambia's cash transfer program found a reduction in curative care for respiratory illnesses in children.[77] Furthermore, no measurable impacts of this cash transfer program were found on maternal healthcare utilization in general.[77] Yet, another study reported that among women that already had access to health care, cash transfers were positively associated with an increased likelihood of giving birth where a skilled healthcare professional was present.[13]

In a systematic review conducted in Latin America, conditional cash transfers were found effective in increasing the use of preventive services, improving immunization coverage, certain health outcomes and in encouraging healthy behaviour.[76]

An important limitation with prior studies examining the impact of cash transfer programs on healthcare utilization is that they have not accounted for cash transfer recipients' economic preferences and how these preferences might amplify or dampen the intended impacts of the cash transfer program. We address this gap in the literature and examined whether two measures of economic preference, time and risk preference, moderate cash transfer program effects on children's healthcare utilization.

3.1.1. Time Preference

Time preference is the extent to which an individual discounts future benefits and costs such that their preferences for current consumption of a good or service is determined by their valuation of future consumption.[78,79] When a caregiver receives a cash transfer, they may evaluate tradeoffs between the associated cost of healthcare utilization in the near term and their expectation of future costs and benefits for their children and families.[79] Consequently, their decision to spend money and time for healthcare in the present period will depend on whether they value the future benefit of using the healthcare services. The extant literature supports the theory that time preferences affect health seeking behaviour.[79] An empirical assessment of time preference is usually defined using a discount rate,[78] where a lower discount rate suggests a preference for higher future benefits compared to immediate smaller ones. In a study among adults in the United States, those with higher discount rates used fewer preventive services such as mammograms, flu shots, pap smears, dental visits and cholesterol testing.[80] Yet, the evidence on time preference and

healthcare use in sub-Saharan Africa is limited. The only related study was conducted in South Africa, and it found that individuals with higher discount rates were in worse health.[81] However, as suggested by data from the US, time preference may relate to health via its influence on decisions about preventive care utilization. The economic framework for time preference and healthcare use is presented in Appendix B1.2.

3.1.2. Risk Preference

Risk preference reflects an individual's preference for a certain payoff (or loss) to an uncertain one.[82] Upon receipt of a cash transfer, a caregiver's decision to invest in the child's health depends on the value they place on the benefit they can derive from the cash compared to that of investing in preventive healthcare services to reduce the probability of loss in income associated with a child becoming ill. In addition, there are competing demands and an associated opportunity cost of investing the cash transfer in healthcare for a child. Therefore, as caregivers vary on the degree to which they are willing to pay for preventive healthcare services to reduce future potential income losses due to child illness, a caregiver's risk preference may affect their health seeking behavior.[83] Evidence suggests that being risk averse (i.e., less willing to take risks) is associated with using more healthcare services.[84–86] A study conducted in Nigeria found that individuals who were more risk averse were more likely to have higher malaria care-seeking behavior and have higher willingness-to-pay for the recommended care.[87] Among elderly adults in Germany, less risk averse individuals were less likely to have physician visits, physical therapy and take prescribed medications.[85] Similarly, other research examining nonelderly adults in the US found that adults who were more risk averse used more preventative services.[86] The economic framework for risk preference and healthcare use is presented in Appendix B1.3.

3.1.3. The Present Study

Despite the theoretical and empirical evidence that economic preferences may be associated with healthcare use, there is no evidence assessing how these preferences affect cash transfer program impacts on child healthcare utilization. To address this gap, we leveraged five years of evaluation data for the CT-OVC to assess whether caregiver's time and risk preferences moderate the impact of cash transfers on children's healthcare utilization. We hypothesized that a caregiver with a low discount rate who receives a cash transfer may increase their child's healthcare utilization as they value the future benefit of healthcare utilization enough to spend current income on healthcare services, as opposed to using the income on goods and services providing smaller potential benefits sooner. Similarly, receipt of a cash transfer by a more risk averse caregiver may impact child healthcare utilization as they are more willing to invest in preventive care services to reduce the probability of future losses due to illness or the magnitude of loss in the event of an illness. Appendix B1.4 provides the conceptual model for our hypothesis. This study adds to the literature in two important ways. First, it contributes to the limited literature documenting the impact of cash transfers on children's healthcare use for sub-Saharan Africa. Second, this study is the first to analyze the role of caregiver's preferences in the relationship between cash transfer receipt and use of healthcare services for their children.

3.2. Methods

3.2.1. Data

Our study utilized impact evaluation data for the cash transfer for orphans and vulnerable children (CT-OVC) implemented in Kenya.[88] The CT-OVC began as a pilot study in 2004. Prior

to its expansion in 2007, a baseline household survey was conducted using a longitudinal cluster randomized design study by the United Nations Children's Fund (UNICEF) and Oxford Policy Management.[66] A follow-up survey was conducted after 24-months and 48-months, that is, in 2009 and 2011 respectively.[89] The evaluation took place in seven districts in Kenya: Garissa, Homabay, Kisumu, Kwale, Migori, Nairobi and Suba districts. These districts were identified by the Government of Kenya's Department of Children's Services (DCS) and scheduled for inclusion in the expansion of the CT-OVC.[66] Four eligible locations in each district were selected as eligible to be part of the CT-OVC. However, financial constraints limited the roll-out of the CT-OVC to all locations simultaneously, such that only two of the four locations were randomized to the initial expansion and others would serve as the control locations.[66]

Targeting of the households in the intervention locations was based on the standard program operation guidelines of the CT-OVC.[66] Specifically, a committee of individuals in each community was formed to identify households based on selected poverty indicators and having an orphan or vulnerable child in the household.[15] To reduce selection bias the list of households identified by the committee was reviewed by the Ministry of Gender, Children and Social Development Community to confirm eligibility using a questionnaire to rank households.[15] In the control locations, however, targeting of households was based on a simulation that identified a sample of households that were comparable to those identified as eligible in the treatment groups.[66] The CT-OVC impact evaluation data collected individual, household, socioeconomic status and healthcare utilization characteristics in each wave. Additionally, in the 2011 survey, a module to collect individual economic preferences, time preference and risk preference, was included. Further, a community-level questionnaire was administered using focus group discussions in each wave. The community-level data is merged with the individual level data to include healthcare

fees, and facility and worker availability in the analysis. The baseline survey included a random sample of 2,759 households and approximately 15,500 individuals.[88] A total of 2,255 households were surveyed again at follow-up in 2009 (wave 2), a retention rate of 82%.[66]

3.2.2. Sample

Our initial sample comprised 3,594 children aged five years and less and living in a household where a caregiver, identified as the household head, responded to the economic preference module in wave 3. We excluded observations where all outcome data were missing (n=201). The final analytical sample was 3,393.

3.2.3. Child Healthcare Utilization

Child healthcare utilization measures were created based on a combination of data collected from actual health records in the form of a health card and from self-reported measures collected during the time of the interview. A health card for a child is usually provided at a child's birth when delivery happens at a health facility. Records of immunization and weight are usually recorded on this card at every healthcare visit.[90] We created four measures that proxy general child healthcare utilization as binary variables for whether a child (i) has a health card (ii) was weighed by a healthcare worker (iii) sought treatment for diarrhea and (iv) received vitamin A from a healthcare worker. We also created measures for receipt of disease-specific vaccinations as four binary variables for whether a child received (i) any BCG (or tuberculosis) vaccination (ii) any polio vaccination (iii) any DPT/Hep/Flu vaccination and (iv) any measle vaccination. We additionally created two count variables for disease-specific vaccinations: (i) number of polio vaccination and (ii) number DPT/Hep/Flu vaccinations. As not all children's healthcare utilization

outcomes variables were measured in each wave of data, sample sizes of regressions will vary slightly across outcomes. Specifically, seven of the ten outcomes were measured in all three waves and three were measured in two waves. Appendix B2 provides the list of survey questions used to create these outcomes.

3.2.4. Cash Transfer Receipt: CT-OVC

The primary regressor or independent variable was a binary measure to indicate whether a child lived in a household that was in the treatment group (i.e., in a community that was allocated to receive cash transfers via CT-OVC) versus whether they were in a control household.

3.2.5. Economic preferences: Time Preference and Risk Preference

Two measures of economic preference were analyzed in the study: Time preference and risk preference. As the economic preference module was only included in the 2011 survey, we assumed that time and risk preferences do not change over time for the following reasons. Firstly, prior literature has found that the CT-OVC has no association with either time or risk preferences.[91] Secondly, despite other literature finding that preferences change with age,[81] caregivers in our sample are primarily older individuals and a short time period exists between baseline and follow-up (five years). Lastly, the cash transfer represents about 22% of the households' budget in the sample[66] and may therefore not be large enough to shift preferences. Nonetheless, we also created a conservative measure of time and risk preference such that a caregiver is unlikely to move from being more risk averse to less (or having a low discount rate to high).

A measure of time preference was created based on caregiver responses to a hypothetical scenario. Respondents were asked: "Suppose that you suddenly win money in the Lotto. If you

could choose between these payments, which would you choose?" Respondents were then given six options in which they were asked to choose between receiving an amount of money now or a higher amount one month later as follows: "1. Ksh 1500 today or 2. Ksh XX in one month". The amount of money available today was kept constant at Ksh 1500, but the amount they could take instead one month from now varied to the following amounts: Ksh 1250, Ksh 1500, Ksh 3000, Ksh 4500, Ksh 7000, Ksh 9000. We exclude the ksh1500 future payment from the calculation of time preference as this option represents indifference, and we have no information to assess whether a participants choice represents patience or not. Inconsistent responses were set to missing (n=4), such as a respondent choosing to wait for Ksh 1250 but not to wait for Ksh 9000.[92] Following a prior study,[92] we created a binary measure equal to 1 for a caregiver that always choses to wait for the future payment, such that our time preference variable is a measure for having a low discount rate. A low discount rate (time preference =1) indicates preferences for larger, later benefits over sooner, smaller ones.

Risk aversion is a measure of risk preference that reflects an individual who prefers a certain payoff (or loss) to an uncertain one.[82] A measure of risk aversion was created based on the following hypothetical scenario: Now I want to ask how you would respond in a hypothetical game. In this game you can choose to get Ksh 1500 or you can choose to a lottery that will give you a 50% chance of winning an even greater amount or a 50% chance of getting less than Ksh 1500. Which of the lotteries would you prefer over getting Ksh 1500 for certain?" A. 3000 or 0; B. 12000 or 0; C. 7000 or 1000; D. 8000 or 0; E. 2000 or 1000. We created a binary measure of risk aversion as a binary variable equal to 1 for a caregiver who always chose not to take the gamble or has a high risk aversion.

3.2.6. Covariates

Following prior research, we include individual, household and community characteristics that have been found to be associated with healthcare utilization. Individual characteristics include age, gender, education and marital status.[13,93–98] The age of the child and age of the caregiver are both included as a continuous variable. The highest education of the caregiver is included as a categorical variable (no schooling, standard 1-8, Form 1-4, Secondary and above). The marital status of household head is measured as a binary measure (married/living with partner versus not).[94] Gender of the caregiver and of the child are both included as a binary variable equal to 1 for female.

Household characteristics included the number of children living in the household and the number of rooms in the house.[94–97] Considering the targeting of the CT-OVC for extremely poor households, we used the number of rooms in the household as a proxy for household wealth.[99] Community characteristics included distance to the nearest health facility, mobile clinic availability, the cost of vaccination and medicine availability at nearest health facility. [13,94,96,98] The distance to the nearest health facility is created as a categorical variable (0-2km, 2-5km, 5-10km, >10km). A binary measure for whether the nearest health facilities usually offer vaccination was included in the analysis. Mobile clinic availability was a binary measure for whether a health worker is temporarily available in that community to provide healthcare services. Community facility fees for vaccinations for children under the age of 5 was included as a (log-transformed) continuous variable.

3.2.7. Statistical analysis

We used the difference-in-difference approach, a quasi-experimental approach, to estimate the change in child healthcare utilization from baseline to follow-up for children in the treatment group, compared to the change in utilization from baseline to follow-up for children in the control group. The validity of the difference-in-difference approach relies on the parallel trend assumption. The parallel trend assumption means that the trends prior to the intervention are the same across treatment and control groups.[100] While the assumption is not full testable, we compared the differences in children healthcare utilization between the treatment and control groups in the baseline period. We estimated linear probability models for our binary measures and OLS-regression for continuous outcomes. The following equation was estimated:

$$Y_{iht} = \beta_0 + \beta_1 CT_{iht} + \beta_2 Post_{it} + \beta_3 (CT_{iht} * Post_{it}) + \beta X + \lambda + \varepsilon_{iht} \qquad \text{(i)}$$

In *equation (i)* the dependent variable *Y* is child healthcare utilization for individual *i* in household *h* and year *t. CT* is the treatment variable or indicator that child lived in a household that received the CT-OVC and *Post* is a binary measure to indicate the period after baseline. β_3 is the difference-in-difference estimate and coefficient of interest that measures the impact of the cash transfer on child healthcare use. *X* is the set of covariates (at baseline value) as described above and λ represents district fixed effects. To estimate whether time or risk preference moderates the impact of the cash transfer program on child healthcare utilization, we estimated the following triple-difference model using both linear probability model and OLS-regressions:

$$Y_{iht} = \beta_0 + \beta_1 CT_{iht} + \beta_2 Post_{it} + \beta_3 E_h + \beta_4 (CT_{iht} * Post_{it}) + \beta_5 (CT_{iht} * E_h) + \beta_6 (Post_{it} * E_h) + \beta_7 (CT_{iht} * Post_{it} * E_h) + \beta X + \lambda + \varepsilon_{iht} \quad \text{(ii)}$$

In *equation (ii)* E_h reflects caregivers' economic preferences (i.e., either discount rate or risk aversion). The triple-difference coefficient β_7 therefore captures the effect of a caregiver's preferences on the impact of the CT-OVC and child healthcare use. All other variables were as described for *equation (i).* All our regression models cluster standard errors at the household level to correct for multiple children in a household and multiple observations within a household overtime. A significance level of $p<0.05$ was used. All analyses were conducted using StataIC 15.1.

3.2.8. Sensitivity analysis

We conducted several sensitivity analyses. Firstly, the outcomes used in our main analysis are a combination of data obtained from the health card and self-reported measures. Therefore, we run our analysis separately for measures created from the health card and from self-reported measures. Secondly, we test the sensitivity of our results to specification of the risk and time preference. Specifically, we use a continuous measure of time preference as the number of times a caregiver chose to wait for future payment and risk preference as the number of times the gamble was not chosen. Finally, there were baseline differences in demographic characteristics of the caregiver between the treatment and control, we created weights to estimate treatment effects that are more robust. Specifically, we estimated inverse probability weights as the probability of being in the treatment given a set of covariates.[91]

3.3. Results

On average, children in the sample were aged 3 years old while their caregivers were 53 years old (Table 5). The sample mainly comprised caregivers who were female (56%), unmarried (54%) and had low levels of education (about 98% had less than secondary education). Households had about 2 children living in them, and majority (60%) were located about 0-2km from a health facility. About 70% of the sample lived in communities where medicines were always available at the nearest health facility and 52% in areas where healthcare workers were present for part of the week to provide health services. The average rates of child healthcare utilization ranged from 49% to 92%. Majority of children had received DPT, Polio and BCG vaccinations (>89%) but had low levels of receipt of Vitamin A supplements from a healthcare worker. Approximately 65% of children lived in households that received the CT-OVC. Overall, 12% of caregivers had low discount rates while 64% were risk averse.

Table 5: Summary statistics, full sample (n=3393)

Variable	n	mean	SD
Outcomes			
Health card (vaccination card, growth monitoring card)	2,793	0.67	0.47
Received BCG vaccination	2,595	0.90	0.31
Number of times DPT vaccination was received	2,289	2.37	1.24
Received DPT vaccination	2,533	0.89	0.31
Received Polio vaccination	2,600	0.92	0.28
Number of times Polio vaccination was received	2,304	3.07	1.41
Received measles vaccination	2,383	0.80	0.40
Given Vitamin A supplements	2,079	0.49	0.50
Sought treatment for diarrhea	684	0.79	0.41
Any vaccination	2,695	0.90	0.30
Independent variables			
Received CT-OVC	3,390	0.65	0.48
Low discount rate	3,051	0.12	0.32
Risk averse	3,393	0.64	0.48
Covariates			
Child age	3,393	2.65	1.66
Age of household head	3,385	53.68	17.00
Female household head	3,393	0.56	0.50
Highest education of household head*			
No schooling	1,365	40.87	
Standard 1 - 8	1,628	48.74	
Form 1 - 6	312	9.34	
Above secondary	35	1.05	
Married/living together	3,393	0.46	0.50
Number of children	3,393	2.16	1.21
Number of rooms in household	3,393	2.50	1.39
Distance to nearest health facility*			
0-2km	1,978	59.74	
2-5km	880	26.58	
5-10km	274	8.28	
>10km	179	5.41	
Medicine availability at nearest health facility	3,295	0.70	0.46
Cost of vaccinations (kSh)	3,305	0.70	0.46
Mobile clinics available	3,273	0.52	0.50

Generally, healthcare utilization for children was higher in households that received the CT-OVC compared to those in households that did not, although there was no unadjusted significant difference in any of our outcomes at baseline, as expected with random assignment (Table 6). Although we did not test for the parallel trend assumption, this assumption is plausible since we found no significant differences in our measures of children healthcare utilization between treatment and control groups in the baseline period. There were also no significant differences in our measure of discount rate and risk aversion amongst care givers in the treatment and the control groups before adjustment.

Table 6: Baseline characteristics between treatment and control, wave 1

	CT-OVC			No CT-OVC			
	n	**mean**	**SD**	**n**	**mean**	**SD**	**p-values**
Outcomes:							
Health card	365	0.53	0.50	218	0.56	0.50	0.346
Received BCG vaccination	347	0.87	0.34	210	0.82	0.38	0.169
Number of times DPT vaccination was received	305	2.28	1.17	186	2.32	2.51	0.434
Received DPT vaccination	333	0.85	0.35	214	0.83	0.38	0.761
Received Polio vaccination	352	0.89	0.31	216	0.86	0.35	0.216
Number of times Polio vaccination was received	297	3.11	1.52	192	2.84	1.64	0.070
Received measles vaccination	315	0.84	0.37	184	0.83	0.38	0.679
Sought treatment for diarrhea	135	0.76	0.43	76	0.70	0.46	0.391
Given Vitamin A supplements	614	0.45	0.50	342	0.45	0.50	0.990
Independent variables:							
Low discount rate	900	0.12	0.32	325	0.10	0.29	0.135
Risk averse	1,008	0.62	0.48	361	0.64	0.48	0.437
Covariates:							
Child age	647	2.56	1.65	361	2.50	1.65	0.545
Age of household head***	647	58.20	18.71	361	51.87	23.07	0.000
Female household head***	647	0.60	0.49	361	0.45	0.50	0.000
Highest education of household head***							
No schooling	300	47.47		99	28.45		0.000
Standard 1 - 8	282	44.62		207	59.48		
Form 1 - 6	44	6.96		39	11.21		
Above secondary	6	0.95		3	0.86		
Married/living together***	647	0.39	0.49	361	0.56	0.50	0.000
Number of children***	647	2.28	1.63	361	2.06	0.96	0.020
Number of rooms in household	647	2.53	1.52	361	2.37	1.19	0.075
Distance to nearest health facility***							
0-2km	418	64.61		257	71.19		0.000
2-5km	139	21.48		82	22.71		
5-10km	45	6.96		15	4.16		
>10km	45	6.96		7	1.94		
Medicine availability at nearest health facility***	647	0.91	0.29	361	0.82	0.39	
Cost of vaccinations (kSh)***	647	1.83	5.24	361	3.02	3.81	0.000
Mobile clinics available	647	0.50	0.50	329	0.50	0.50	0.770

*** p-value less than 0.05

3.3.1. CT-OVC impact on child healthcare utilization

In our models analyzing the impact of the CT-OVC on our measures of child healthcare utilization, we do not find significant effects in any of our adjusted models (Table 7-8). Although, in the unadjusted models, we found that children that received the cash transfer were more likely to receive vitamin A supplements. Specifically, in the unadjusted model, children that received the cash transfer were estimated to have 0.114 ($p<0.05$) higher probability of receiving a vitamin A supplement from a healthcare worker, other things constant. However, this effect became imprecise when we include covariates in the model. Nonetheless, older children were less likely to have a health card, be weighed by a healthcare worker and receive any vaccination. However, they were also more likely to receive measles vaccination ($\beta=0.079$, $p<0.01$). Children who had female caregivers had received more polio vaccinations ($\beta=0.419$, $p<0.01$) and DPT vaccinations ($\beta=0.288$, $p<0.05$). Similarly, if the caregiver was married/cohabiting the children had higher polio and DPT vaccinations. A caregiver with education above secondary was less likely to seek treatment for diarrhea when compared to those with no schooling.

We found that children living in households where medicine fees are charged for vaccination were less likely to receive vitamin A supplement but more likely to receive any vaccination. Further, those that lived in communities where medicine was always available at the nearest health facility were less likely to receive polio, BCG, DPT and any vaccinations. The further a household from a health facility, the less likely the child was to have a health card, to receive vitamin A supplements and measles vaccination, and had lower polio and DPT vaccinations.

Table 7: CT-OVC impact on proxy measures of healthcare use under-5, Difference-in-difference estimate

	Has Health card		**Weighed by Health Worker**		**Sought treatment for Diarrhea**		**Received vitamins from a healthcare worker**	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
CT	-0.0382	-0.0106	0.0189	0.00902	0.0582	0.0926	0.00118	-0.0199
	(0.0400)	(0.0495)	(0.0305)	(0.0385)	(0.0584)	(0.0804)	(0.0336)	(0.0491)
POST	0.152***	0.334***	0.0308	0.0372	0.0679	-0.0415	0.00175	-0.0422
	(0.0358)	(0.0461)	(0.0327)	(0.0398)	(0.0550)	(0.0835)	(0.0360)	(0.0511)
CT*POST	0.0145	-0.0149	-0.00574	-0.0197	0.0201	0.00364	**0.114****	0.114*
	(0.0450)	(0.0502)	(0.0412)	(0.0492)	(0.0697)	(0.0848)	(0.0454)	(0.0599)
Child Age		-0.0487***		-0.0735***		-0.00889		-0.00808
		(0.00566)		(0.00592)		(0.0112)		(0.00650)
Female Caregiver		-0.0315		0.0179		0.0590		0.109*
		(0.0421)		(0.0508)		(0.0718)		(0.0579)
Caregiver Age		-0.000714		0.000227		0.00203		0.000652
		(0.000758)		(0.000750)		(0.00124)		(0.000936)
Caregiver married/cohabiting		0.00545		-0.0289		0.0397		0.109*
		(0.0414)		(0.0503)		(0.0739)		(0.0565)
Education: ref: No schooling								
Standard 1-8		0.0511*		0.00930		0.0435		0.00439
		(0.0283)		(0.0325)		(0.0427)		(0.0391)
Form 1 -6		-0.0237		0.0424		0.0683		0.0852
		(0.0431)		(0.0485)		(0.0783)		(0.0622)
Above secondary		0.0501		0.0886		-0.796***		-0.0690
		(0.0916)		(0.121)		(0.0839)		(0.120)
HH size		-0.00609		-0.00110		0.00765		0.0111
		(0.00973)		(0.0143)		(0.0139)		(0.0186)
Number of rooms		0.00358		0.00375		-0.0370**		-0.00519
		(0.00770)		(0.0110)		(0.0162)		(0.0127)
ln(Clinic fees)		0.00174		0.000798		0.00192		-0.0072***
		(0.00178)		(0.00242)		(0.00289)		(0.00267)
Mobile clinic availability		0.00557		0.00177		-0.0212		-0.0136
		(0.0228)		(0.0300)		(0.0430)		(0.0352)

Medicine Availability		-0.0519**		-0.0278		0.0484		-0.0109
		(0.0240)		(0.0364)		(0.0471)		(0.0387)
Distance to nearest health facility: ref: 0-2km								
2-5km		-0.0108		0.00596		-0.0500		-0.0370
		(0.0268)		(0.0344)		(0.0471)		(0.0400)
5-10km		-0.0854**		2.24e-05		0.00112		-0.0647
		(0.0408)		(0.0488)		(0.0603)		(0.0618)
>10km		-0.0972**		-0.0584		0.0180		-0.126**
		(0.0438)		(0.0655)		(0.0859)		(0.0628)
District: Ref: Garissa								
Homabay		0.196***		-0.0729		0.0482		-0.0269
		(0.0577)		(0.0665)		(0.0938)		(0.0793)
Kisumu		0.250***		-0.0412		-0.0872		0.0117
		(0.0551)		(0.0679)		(0.0906)		(0.0772)
Kwale		0.423***		0.0915		-0.00303		-0.0457
		(0.0483)		(0.0664)		(0.0942)		(0.0717)
Migori		0.160***		-0.0472		-0.0441		-0.0788
		(0.0570)		(0.0680)		(0.0899)		(0.0766)
Nairobi		0.374***		0.0775		-0.107		0.135*
		(0.0545)		(0.0653)		(0.0919)		(0.0759)
Suba		0.255***		-0.113*		-0.0298		0.0256
		(0.0561)		(0.0638)		(0.0987)		(0.0759)
Constant	0.564***	0.364***	0.279***	0.249	0.697***	-0.241	0.453***	0.240
	(0.0316)	(0.126)	(0.0244)	(0.162)	(0.0467)	(0.262)	(0.0269)	(0.170)
Observations	2,790	2,607	2,160	2,073	682	633	2,076	1,992
R-squared	0.020	0.196	0.001	0.103	0.015	0.098	0.012	0.052

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8: CT-OVC impact on receiving disease-specific vaccinations, Difference-in-difference estimate

	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT	0.038	0.037	0.037	0.048	0.267*	0.275	0.025	0.025	-0.075	-0.082	-0.001	-0.019
	(0.028)	(0.040)	(0.025)	(0.036)	(0.137)	(0.177)	(0.028)	(0.041)	(0.121)	(0.238)	(0.038)	(0.040)
POST	0.1***	0.059	0.1***	0.044	0.152	0.057	0.07**	0.046	-0.002	-0.093	-0.1**	-0.1**
	(0.025)	(0.038)	(0.023)	(0.034)	(0.124)	(0.176)	(0.026)	(0.040)	(0.110)	(0.238)	(0.034)	(0.036)
CT*POST	-0.030	-0.038	-0.026	-0.027	-0.142	-0.156	-0.010	-0.013	0.114	0.080	0.068	0.049
	(0.032)	(0.042)	(0.029)	(0.038)	(0.155)	(0.190)	(0.032)	(0.041)	(0.137)	(0.225)	(0.043)	(0.041)
Child Age		-0.006		-0.001		0.010		-0.000		0.008		0.1***
		(0.004)		(0.004)		(0.022)		(0.005)		(0.016)		(0.006)
Female Caregiver		0.027		0.035		0.4***		0.039		0.29**		0.038
		(0.035)		(0.032)		(0.152)		(0.036)		(0.122)		(0.036)
Caregiver Age		-0.000		-0.00*		-0.003		-0.001		-0.000		0.001
		(0.001)		(0.001)		(0.003)		(0.001)		(0.002)		(0.001)
Caregiver married/cohabiting		0.026		0.046		0.4***		0.045		0.2**		0.016
		(0.034)		(0.032)		(0.149)		(0.035)		(0.119)		(0.035)
Education: ref: No schooling												
Standard 1-8		0.013		0.011		0.080		0.029		0.081		-0.015
		(0.020)		(0.018)		(0.095)		(0.022)		(0.083)		(0.023)
Form 1 -6		0.001		0.014		0.070		0.017		0.041		0.021
		(0.029)		(0.025)		(0.145)		(0.031)		(0.111)		(0.035)
Above secondary		-0.002		0.022		0.389		0.063		0.228		0.069
		(0.058)		(0.054)		(0.248)		(0.057)		(0.200)		(0.061)
HH size		-0.007		0.001		-0.026		0.004		-0.013		-0.008
		(0.008)		(0.007)		(0.039)		(0.008)		(0.032)		(0.009)
Number of rooms		0.006		0.006		0.024		0.005		0.011		0.011

		(0.006)		(0.006)		(0.028)		(0.006)		(0.028)		(0.008)
Ln(Clinic fees)		0.002		0.002*		0.001		0.00**		0.006		-0.00*
		(0.001)		(0.001)		(0.006)		(0.001)		(0.005)		(0.001)
Mobile clinic availability		0.019		0.009		0.047		0.018		0.096		0.025
		(0.018)		(0.016)		(0.082)		(0.017)		(0.065)		(0.021)
Medicine Availability		-0.1**		-0.1**		-0.15*		-0.1**		-0.14*		0.005
		(0.020)		(0.018)		(0.089)		(0.020)		(0.070)		(0.023)
Distance to nearest health facility: ref: 0-2km												
2-5km		-0.015		-0.005		-0.130		0.002		-0.112		-0.1**
		(0.020)		(0.018)		(0.091)		(0.020)		(0.075)		(0.023)
5-10km		-0.003		-0.018		-0.28*		-0.007		-0.2**		-0.1**
		(0.031)		(0.024)		(0.149)		(0.026)		(0.107)		(0.041)
>10km		-0.061		-0.067		-0.4**		-0.08*		-0.3**		-0.1**
		(0.042)		(0.042)		(0.159)		(0.043)		(0.153)		(0.048)
District: Ref: Garissa												
Homabay		0.007		0.030		0.49**		0.013		0.328*		-0.053
		(0.052)		(0.048)		(0.220)		(0.052)		(0.168)		(0.057)
Kisumu		0.1**		0.1***		0.9***		0.1***		0.7***		-0.069
		(0.049)		(0.044)		(0.197)		(0.047)		(0.152)		(0.048)
Kwale		0.2***		0.2***		1.3***		0.2***		1.1***		0.078*
		(0.046)		(0.041)		(0.180)		(0.043)		(0.172)		(0.046)
Migori		0.046		0.062		0.47**		0.016		0.278*		-0.020
		(0.051)		(0.044)		(0.209)		(0.053)		(0.168)		(0.049)
Nairobi		0.1***		0.1***		1.2***		0.2***		0.9***		-0.016
		(0.045)		(0.041)		(0.195)		(0.044)		(0.141)		(0.048)
Suba		0.056		0.109**		0.670***		0.1**		0.590***		-0.009
		(0.050)		(0.044)		(0.203)		(0.047)		(0.157)		(0.051)
Constant	0.830***	0.676***	0.856***	0.734***	2.853***	1.262**	0.828***	0.615***	2.358***	0.719	0.842***	0.609***
	(0.022)	(0.110)	(0.020)	(0.096)	(0.109)	(0.547)	(0.023)	(0.129)	(0.097)	(0.500)	(0.031)	(0.101)

Observations	2,428	2,427	2,434	2,433	2,157	2,156	2,369	2,368	2,140	2,139	2,226	2,225
R-squared	0.005	0.043	0.005	0.045	0.003	0.088	0.007	0.057	0.001	0.077	0.007	0.136

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

3.3.2. Time Preference effect on the impact of CT-OVC on child healthcare utilization

On average, there was a significant positive program impact of the cash transfer on healthcare utilization for children that had caregivers with a low discount rate compared to those with a higher discount rate (Table 9-10). Time preference moderated the impact of the CT-OVC on child healthcare utilization in five of the ten measures of child healthcare utilization in both the adjusted and unadjusted models in the expected direction. In the adjusted model for general healthcare use measure, children that received the cash transfer and had a caregiver with a low discount rate were estimated to have a 0.398 ($p<0.01$) higher probability of having a health card, other things constant. Despite these findings supporting our hypothesis that time discount rates of caregivers moderate the cash transfer impacts on child healthcare utilization, the estimate is suggesting a huge difference in the probability that may not be plausible. In addition, the other estimates from the triple-difference model are counterintuitive. For instance, children in the post period who had a caregiver and those with a low discount rate had a high probability of having a healthcare card [$\beta=0.312$ ($p<0.01$) and $\beta=0.362$ ($p<0.01$), respectively]. However, those children in the post period and with a caregiver with a low discount rate had a lower probability ($\beta=-0.297$, $p<0.01$) of having a healthcare card.

Of the six measures on disease specific vaccinations, we find a significant effect amongst four of our measures (Table 10). In the unadjusted models, children who lived in a household that received the CT-OVC and had a caregiver with a low discount rate were more likely to receive a vaccination for BCG, polio and DPT. This effect was significant even after we controlled for other variables. Specifically, children that received the cash transfer and had a caregiver with a low discount rate were more likely to receive a BCG vaccination ($\beta=0.262$, $p<0.05$), polio vaccination ($\beta=0.269$, $p<0.01$) and DPT vaccination ($\beta=0.331$, $p<0.01$). In addition, children who lived in a

household that received the CT-OVC and had a caregiver with a low discount rate also had a higher number of polio vaccinations (β=1.117, $p<0.05$) on average. The estimates from the models on disease specific measures are also counterintuitive. The counterintuitive findings could be explained by the small sample size ($n<18$) of children in the baseline period that did not receive the CT-OVC and had a caregiver who had a low discount rate but had the highest probability of experiencing the outcome. This results in a negative difference when compared to those that received the CT-OVC in the post period and had caregivers with a low discount rate.

Table 9: Time Preference Effect on CT-OVC impact on general measures of healthcare use under-5; Triple-Difference estimates

	Has Health card		**Sought treatment for Diarrhea**		**Weighed by Health Worker**		**Received vitamins from a healthcare worker**	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
CT	-0.00713	0.000228	-0.00871	0.0198	0.00829	-0.0180	0.00264	-0.00210
	(0.0449)	(0.0548)	(0.0674)	(0.0896)	(0.0374)	(0.0538)	(0.0342)	(0.0431)
Time Preference	0.283**	0.312***	-0.491***	-0.312	-0.0202	-0.0869	0.0442	0.0222
	(0.119)	(0.108)	(0.154)	(0.221)	(0.0953)	(0.120)	(0.0870)	(0.0954)
Post	0.173***	0.362***	0.0313	-0.117	-0.00287	-0.0613	0.0532	0.0527
	(0.0399)	(0.0512)	(0.0630)	(0.0859)	(0.0397)	(0.0553)	(0.0361)	(0.0456)
CT*Post	-0.0214	-0.0439	0.0770	0.0923	0.142***	0.150**	0.00210	-0.00970
	(0.0505)	(0.0562)	(0.0806)	(0.0917)	(0.0505)	(0.0655)	(0.0460)	(0.0553)
CT* Time	-0.351**	-0.344**	0.605***	0.560**	-0.0768	-0.0342	0.0126	0.0448
	(0.141)	(0.139)	(0.196)	(0.247)	(0.114)	(0.141)	(0.104)	(0.124)
Time*Post	-0.349**	-0.297***	0.119	-0.00829	0.131	0.189	-0.222*	-0.128
	(0.136)	(0.0964)	(0.204)	(0.275)	(0.126)	(0.161)	(0.117)	(0.122)
CT* Time * Post	**0.473*** **	**0.398*** **	-0.259	-0.317	-0.134	-0.159	0.0976	0.0192
	(0.161)	(0.137)	(0.247)	(0.306)	(0.152)	(0.192)	(0.140)	(0.163)
Child Age		-0.050***		-0.00506		-0.0110		-0.073***
		(0.00592)		(0.0124)		(0.00687)		(0.00624)
Female Caregiver		-0.0167		0.132*		0.0963		0.00853
		(0.0436)		(0.0689)		(0.0595)		(0.0533)
Caregiver Age		-0.000464		0.00306**		0.000193		0.000557
		(0.000780)		(0.00134)		(0.000966)		(0.000787)
Caregiver married/cohabiting		0.0188		0.0857		0.114**		-0.0365
		(0.0424)		(0.0700)		(0.0581)		(0.0525)
Education: ref: No schooling								
Standard 1-8		0.0605**		0.0868*		0.00557		0.00645
		(0.0299)		(0.0501)		(0.0393)		(0.0340)
Form 1 -6		-0.00900		0.149*		0.0722		0.0333
		(0.0463)		(0.0874)		(0.0654)		(0.0528)
Above secondary		0.0574		-0.714***		-0.113		0.0505

		(0.102)		(0.164)		(0.125)	(0.121)
HH size		-0.00441		-0.00700		0.0219	-0.00372
		(0.0104)		(0.0158)		(0.0188)	(0.0160)
Number of rooms		2.80e-05		-0.053***		-0.00220	0.000981
		(0.00856)		(0.0173)		(0.0130)	(0.0108)
Clinic fees		0.00256		0.00119		-0.0073***	-0.000129
		(0.00189)		(0.00328)		(0.00278)	(0.00258)
Mobile clinic availability		0.00701		-0.0167		-0.0330	0.00594
		(0.0239)		(0.0447)		(0.0373)	(0.0321)
Medicine Availability		-0.0418*		0.0326		-0.0148	-0.0202
		(0.0249)		(0.0544)		(0.0414)	(0.0391)
Distance to nearest health facility: ref: 0-2km							
2-5km		0.00796		-0.00554		-0.0356	0.0127
		(0.0278)		(0.0521)		(0.0410)	(0.0367)
5-10km		-0.0635		-0.0337		-0.0522	-0.0309
		(0.0441)		(0.0671)		(0.0632)	(0.0510)
>10km		-0.112**		0.0591		-0.112	-0.0311
		(0.0474)		(0.0936)		(0.0705)	(0.0735)
District: Ref: Garissa							
Homabay		0.176***		-0.00142		0.0127	-0.0570
		(0.0605)		(0.106)		(0.0851)	(0.0733)
Kisumu		0.231***		-0.126		0.0415	-0.0225
		(0.0578)		(0.0958)		(0.0830)	(0.0747)
Kwale		0.414***		-0.0392		0.000825	0.0695
		(0.0523)		(0.107)		(0.0810)	(0.0734)
Migori		0.121**		-0.0805		-0.0382	-0.0353
		(0.0602)		(0.103)		(0.0818)	(0.0754)
Nairobi		0.364***		-0.171		0.176**	0.0721
		(0.0571)		(0.106)		(0.0819)	(0.0722)
Suba		0.230***		-0.0898		0.0731	-0.0988
		(0.0588)		(0.111)		(0.0818)	(0.0708)
Constant	0.540***	0.311**	0.741***	-0.468*	0.454***	0.218	0.278*** 0.214
	(0.0354)	(0.131)	(0.0537)	(0.283)	(0.0296)	(0.184)	(0.0270) (0.176)

Observations	2,508	2,355	582	548	1,872	1,800	1,948	1,877
R-squared	0.023	0.205	0.048	0.141	0.020	0.060	0.006	0.100
Total impact – Low discount rate	0.451***	0.391***	-0.182	-0.166	0.099	0.09	0.007	-0.009
	(0.153)	(0.123)	(0.233)	(0.295)	(0.132)	(0.951)	(0.14)	(0.961)
Total impact – High discount rate	-0.0214	-0.0439	0.0770	0.0923	**0.142*** **	0.150**	0.00210	-0.00970
	(0.0505)	(0.0562)	(0.0806)	(0.0917)	(0.0505)	(0.0655)	(0.0460)	(0.0553)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; #program impact is the sum of the difference-in-difference estimate and the triple-difference estimate; Program impacts estimated using the lincolm command.

Table 10: Time Preference Effect CT-OVC impact on disease specific vaccinations under-5; Triple-difference estimates

	Received BCG vaccination		**Received Polio vaccination**		**Number of polio vaccinations received**		**Received DPT vaccination**		**Number of DPT received**		**Received Measles vaccination**	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
CT	0.08***	0.09**	0.08***	0.09**	0.48***	0.48**	0.07**	0.069	0.015	-0.006	0.000	-0.013
	(0.031)	(0.043)	(0.028)	(0.040)	(0.154)	(0.198)	(0.031)	(0.046)	(0.138)	(0.292)	(0.043)	(0.046)
Time Preference	0.185**	0.2***	0.166**	0.2***	0.715*	0.8***	0.19**	0.2***	0.352	0.474	0.103	0.117*
	(0.077)	(0.038)	(0.070)	(0.035)	(0.365)	(0.311)	(0.078)	(0.040)	(0.325)	(0.294)	(0.103)	(0.070)
Post	0.09***	0.077*	0.08***	0.073*	0.242*	0.180	0.1***	0.081*	0.002	-0.066	-0.09**	-0.1***
	(0.027)	(0.042)	(0.025)	(0.039)	(0.137)	(0.194)	(0.028)	(0.044)	(0.124)	(0.287)	(0.039)	(0.040)
CT*Post	-0.064*	-0.075	-0.07**	-0.075*	-0.312*	-0.328	-0.063*	-0.068	0.033	0.006	0.087*	0.060
	(0.034)	(0.046)	(0.031)	(0.043)	(0.173)	(0.214)	(0.035)	(0.046)	(0.155)	(0.279)	(0.048)	(0.046)
CT * Time	-0.3***	-0.3***	-0.21**	-0.2***	-1.3***	-1.1**	-0.24**	-0.2***	-0.688*	-0.624	-0.123	-0.103
	(0.093)	(0.083)	(0.085)	(0.076)	(0.457)	(0.414)	(0.096)	(0.081)	(0.405)	(0.379)	(0.126)	(0.103)
Time*Post	-0.21**	-0.2***	-0.18**	-0.19**	-0.8**	-0.9**	-0.2***	-0.3***	-0.470	-0.548	-0.091	-0.126
	(0.089)	(0.076)	(0.081)	(0.074)	(0.432)	(0.320)	(0.091)	(0.076)	(0.383)	(0.356)	(0.120)	(0.105)
CTOVC * Time * Post	**0.273****	**0.26****	**0.3*****	**0.3*****	**1.205****	**1.12****	**0.3*****	**0.3*****	0.720	0.628	-0.020	0.003
	(0.106)	(0.107)	(0.097)	(0.101)	(0.530)	(0.447)	(0.110)	(0.106)	(0.469)	(0.442)	(0.145)	(0.131)
Child Age		-0.007		-0.003		0.004		-0.001		0.005		0.08**
		(0.005)		(0.004)		(0.024)		(0.005)		(0.018)		(0.006)
Female Caregiver		0.036		0.036		0.5***		0.052		0.3***		0.034
		(0.035)		(0.034)		(0.160)		(0.036)		(0.123)		(0.039)
Caregiver Age		-0.000		-0.001*		-0.003		-0.001		-0.000		0.001
		(0.001)		(0.001)		(0.003)		(0.001)		(0.002)		(0.001)
Married/cohabiting		0.040		0.048		0.46**		0.054		0.27**		0.012
		(0.034)		(0.034)		(0.156)		(0.035)		(0.120)		(0.037)
Education: ref: No schooling												
Standard 1-8		0.019		0.013		0.082		0.036		0.091		-0.022
		(0.020)		(0.019)		(0.100)		(0.023)		(0.087)		(0.025)
Form 1 -6		0.016		0.024		0.148		0.032		0.083		0.025
		(0.029)		(0.026)		(0.151)		(0.032)		(0.117)		(0.037)
Secondary+		-0.005		0.021		0.389		0.070		0.227		0.062

		(0.064)		(0.059)		(0.274)		(0.063)		(0.225)		(0.068)
HH size		-0.005		0.002		-0.025		0.005		-0.021		-0.010
		(0.008)		(0.008)		(0.042)		(0.009)		(0.036)		(0.010)
Number of rooms		0.006		0.006		0.015		0.007		0.010		0.013
		(0.007)		(0.007)		(0.033)		(0.007)		(0.034)		(0.009)
Clinic fees		0.001		0.002*		0.001		0.00**		0.006		-0.002
		(0.001)		(0.001)		(0.007)		(0.001)		(0.005)		(0.002)
Mobile clinic availability		0.021		-0.003		0.039		0.013		0.096		0.033
		(0.019)		(0.017)		(0.089)		(0.018)		(0.071)		(0.022)
Medicine Availability		-0.05**		-0.05**		-0.149		-0.05**		-0.141*		-0.020
		(0.020)		(0.019)		(0.092)		(0.021)		(0.074)		(0.024)
Distance to nearest health facility: ref: 0-2km												
2-5km		-0.019		-0.010		-0.127		0.000		-0.101		-0.06**
		(0.022)		(0.019)		(0.097)		(0.022)		(0.081)		(0.024)
5-10km		0.011		-0.019		-0.27*		-0.002		-0.23**		-0.2***
		(0.027)		(0.025)		(0.159)		(0.027)		(0.117)		(0.044)
>10km		-0.059		-0.075*		-0.4**		-0.090*		-0.314*		-0.11**
		(0.045)		(0.045)		(0.171)		(0.046)		(0.171)		(0.052)
District: Ref: Garissa												
Homabay		0.030		0.034		0.59**		0.010		0.331*		-0.046
		(0.055)		(0.051)		(0.233)		(0.055)		(0.181)		(0.061)
Kisumu		0.13**		0.1***		0.9***		0.13**		0.7***		-0.051
		(0.053)		(0.048)		(0.208)		(0.050)		(0.164)		(0.054)
Kwale		0.2***		0.2***		1.3***		0.2***		1.0***		0.077
		(0.050)		(0.046)		(0.196)		(0.047)		(0.196)		(0.052)
Migori		0.065		0.057		0.53**		0.006		0.241		-0.016
		(0.056)		(0.048)		(0.226)		(0.057)		(0.184)		(0.056)
Nairobi		0.2***		0.2***		1.3***		0.2***		0.8***		-0.000
		(0.050)		(0.044)		(0.205)		(0.047)		(0.153)		(0.053)
Suba		0.081		0.12**		0.8***		0.11**		0.6***		0.007
		(0.055)		(0.048)		(0.216)		(0.050)		(0.170)		(0.056)
Constant	0.82***	0.7***	0.8***	0.8***	2.76***	1.26**	0.8***	0.6***	2.35***	0.809	0.84***	0.6***
	(0.024)	(0.107)	(0.022)	(0.098)	(0.122)	(0.557)	(0.025)	(0.128)	(0.111)	(0.506)	(0.035)	(0.108)
Observations	2,318	2,182	2,324	2,189	2,052	1,935	2,267	2,134	2,042	1,924	2,132	2,006
R-squared	0.011	0.087	0.011	0.091	0.010	0.108	0.012	0.097	0.003	0.097	0.012	0.144

Total impact – Low discount rate	**0.173***	**0.172***	**0.183****	**0.19****	**0.891***	**0.79****	**0.216**	0.24**	0.652	0.559	0.069	0.064
	(0.082)	**(0.098)**	**(0.900)**	**(0.092)**	**(0.490)**	**(-.396)**	**(0.104)**	(0.099)	(0.437)	(0.328)	(0.135)	(0.121)
Total impact – High discount rate	-0.064*	-0.075	-0.07**	-0.075*	-0.312*	-0.328	-0.063*	-0.068	0.033	0.006	0.087*	0.060
	(0.034)	(0.046)	(0.031)	(0.043)	(0.173)	(0.214)	(0.035)	(0.046)	(0.155)	(0.279)	(0.048)	(0.046)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1#program impact is the sum of the difference-in-difference estimate and the triple-difference estimate. Program impacts estimated using the lincolm command.

3.3.3. Risk Preference effect on the impact of CT-OVC on child healthcare utilization

In the adjusted models on the impact of CT-OVC on child healthcare utilization by risk preference, we do not find any significant associations (Table 11-12). Although, in one of the unadjusted models, we find that children whose caregiver was risk averse and received the CT-OVC had a lower number of DPT vaccinations received (β=-0.553, $p<0.05$) on average, contrary to our hypothesis. However, this effect became imprecise in the adjusted models.

Table 11: Risk Preference Effect on CT-OVC impact on general measures of healthcare use under-5; Triple-Difference estimates

	Has Health card		Sought treatment for Diarrhea		Weighed by Health Worker		Received vitamins from a healthcare worker	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
CT	0.00621	0.0286	0.0171	0.123	-0.0849	-0.0894	0.0141	-0.0233
	(0.0652)	(0.0795)	(0.0960)	(0.143)	(0.0559)	(0.0788)	(0.0503)	(0.0679)
Risk Preference	-0.0960	-0.00851	0.0863	0.164	-0.0524	-0.0178	-0.0238	-0.0343
	(0.0655)	(0.0805)	(0.0968)	(0.143)	(0.0565)	(0.0783)	(0.0508)	(0.0656)
Post	0.0740	0.286***	0.121	0.0583	-0.0491	-0.0668	0.0228	0.0155
	(0.0586)	(0.0680)	(0.0877)	(0.131)	(0.0600)	(0.0754)	(0.0541)	(0.0668)
CT*Post	-0.0182	-0.0524	0.0656	-0.0458	0.222***	0.198**	0.000642	0.00664
	(0.0735)	(0.0806)	(0.112)	(0.156)	(0.0752)	(0.0962)	(0.0679)	(0.0834)
CT * Risk	-0.0754	-0.0662	0.0655	-0.0411	0.137*	0.111	0.00686	0.0513
	(0.0824)	(0.0979)	(0.121)	(0.168)	(0.0699)	(0.0981)	(0.0633)	(0.0810)
Risk*Post	0.124*	0.0812	-0.0828	-0.163	0.0791	0.0371	0.0122	0.0344
	(0.0739)	(0.0813)	(0.113)	(0.148)	(0.0750)	(0.0969)	(0.0680)	(0.0802)
CT* Risk* Post	0.0559	0.0578	-0.0731	0.0742	-0.171*	-0.134	-0.00904	-0.0424
	(0.0929)	(0.101)	(0.143)	(0.183)	(0.0943)	(0.122)	(0.0855)	(0.104)
Child Age		-0.049***		-0.00886		-0.00795		-0.073***
		(0.00563)		(0.0113)		(0.00655)		(0.00595)
Female Caregiver		-0.0358		0.0458		0.111*		0.0187
		(0.0417)		(0.0718)		(0.0575)		(0.0509)
Caregiver Age		-0.000745		0.00187		0.000605		0.000245
		(0.000769)		(0.00126)		(0.000938)		(0.000756)
Caregiver married/cohabiting		0.00158		0.0355		0.111**		-0.0288
		(0.0409)		(0.0736)		(0.0559)		(0.0503)
Education: ref: No schooling								
Standard 1-8		0.0554**		0.0364		0.00129		0.00952
		(0.0282)		(0.0431)		(0.0387)		(0.0327)
Form 1 -6		-0.0230		0.0712		0.0841		0.0417
		(0.0434)		(0.0793)		(0.0621)		(0.0482)
Secondary +		0.0493		-0.786***		-0.0669		0.0898
		(0.0907)		(0.102)		(0.123)		(0.122)

HH size		-0.00666		0.00717		0.0132		-0.000666
		(0.00957)		(0.0142)		(0.0180)		(0.0144)
Number of rooms		0.00517		-0.0364**		-0.00449		0.00382
		(0.00785)		(0.0169)		(0.0126)		(0.0111)
Clinic fees		0.00178		0.00218		-0.0073***		0.000769
		(0.00177)		(0.00290)		(0.00267)		(0.00243)
Mobile clinic availability		0.00377		-0.0189		-0.0125		0.00177
		(0.0226)		(0.0439)		(0.0354)		(0.0299)
Medicine Availability		-0.0459*		0.0495		-0.00923		-0.0268
		(0.0240)		(0.0478)		(0.0387)		(0.0365)
Distance to nearest health facility: ref: 0-2km								
2-5km		-0.00932		-0.0338		-0.0295		0.00730
		(0.0268)		(0.0471)		(0.0402)		(0.0343)
5-10km		-0.0774*		0.0120		-0.0659		0.00128
		(0.0409)		(0.0630)		(0.0619)		(0.0490)
>10km		-0.0939**		0.0154		-0.121*		-0.0575
		(0.0436)		(0.0860)		(0.0637)		(0.0656)
District: Ref: Garissa								
Homabay		0.195***		0.0716		-0.0115		-0.0683
		(0.0587)		(0.0956)		(0.0804)		(0.0678)
Kisumu		0.252***		-0.0595		0.0259		-0.0383
		(0.0562)		(0.0901)		(0.0779)		(0.0684)
Kwale		0.431***		0.0294		-0.0268		0.0956
		(0.0498)		(0.0962)		(0.0726)		(0.0670)
Migori		0.162***		-0.0192		-0.0649		-0.0438
		(0.0583)		(0.0903)		(0.0773)		(0.0689)
Nairobi		0.384***		-0.0735		0.155**		0.0823
		(0.0556)		(0.0934)		(0.0760)		(0.0666)
Suba		0.257***		-0.0120		0.0410		-0.109*
		(0.0564)		(0.0997)		(0.0769)		(0.0646)
Constant	0.625***	0.371***	0.643***	-0.355	0.487***	0.227	0.295***	0.263
	(0.0521)	(0.130)	(0.0769)	(0.276)	(0.0456)	(0.176)	(0.0406)	(0.167)
Observations	2,790	2,607	682	633	2,076	1,992	2,160	2,073

R-squared	0.025	0.200	0.023	0.106	0.015	0.054	0.001	0.103
Total impact – High risk preference	0.038	0.03	-0.007	0.016	-0.008	-0.036	0.051	0.064
	(0.06)	(0.06)	(0.089)	(0.095)	(0.052)	(0.061)	(0.056)	(0.076)
Total impact – Low risk preference	-0.0182	-0.0524	0.0656	-0.0458	0.222***	0.198**	0.000642	0.00664
	(0.0735)	(0.0806)	(0.112)	(0.156)	(0.0752)	(0.0962)	(0.0679)	(0.0834)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; #program impact is the sum of the difference-in-difference estimate and the triple-difference estimate; Program impacts estimated using the lincolm command.

Table 12: Risk Preference Effect CT-OVC impact on disease specific vaccinations under-5, Triple-difference estimates

	Received BCG vaccination		**Received Polio vaccination**		**Number of polio vaccinations received**		**Received DPT vaccination**		**Number of DPT received**		**Received Measles vaccination**	
VARIABLES	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
CT	0.043	0.037	0.026	0.032	0.251	0.174	0.021	0.012	-0.43**	-0.503	-0.024	-0.053
	(0.046)	(0.063)	(0.041)	(0.053)	(0.224)	(0.266)	(0.046)	(0.057)	(0.197)	(0.55)	(0.061)	(0.052)
Risk Preference	-0.036	0.001	-0.050	-0.011	-0.332	-0.153	-0.072	-0.028	-0.8***	-0.645	-0.075	-0.079
	(0.047)	(0.065)	(0.042)	(0.056)	(0.227)	(0.280)	(0.047)	(0.060)	(0.202)	(0.53)	(0.063)	(0.061)
Post	0.053	0.058	0.047	0.050	0.059	0.035	0.036	0.034	-0.5***	-0.499	-0.12**	-0.2***
	(0.042)	(0.060)	(0.038)	(0.049)	(0.205)	(0.252)	(0.042)	(0.053)	(0.181)	(0.53)	(0.055)	(0.044)
CT*Post	-0.062	-0.079	-0.054	-0.062	-0.181	-0.191	-0.025	-0.031	0.49**	0.458	0.121*	0.106*
	(0.052)	(0.069)	(0.047)	(0.058)	(0.253)	(0.293)	(0.052)	(0.060)	(0.223)	(0.54)	(0.068)	(0.057)
CT * Risk	-0.011	-0.000	0.016	0.027	-0.002	0.161	0.002	0.019	0.53**	0.657	0.035	0.055
	(0.058)	(0.079)	(0.052)	(0.068)	(0.283)	(0.337)	(0.059)	(0.076)	(0.249)	(0.56)	(0.078)	(0.076)
Risk*Post	0.027	0.003	0.018	-0.010	0.138	0.034	0.046	0.020	0.8***	0.649	0.059	0.070
	(0.052)	(0.070)	(0.047)	(0.062)	(0.256)	(0.305)	(0.053)	(0.064)	(0.22)	(0.53)	(0.070)	(0.066)
CT* Risk * Post	0.053	0.061	0.046	0.052	0.096	0.056	0.027	0.028	**-0.55****	-0.589	-0.081	-0.089
	(0.065)	(0.087)	(0.059)	(0.077)	(0.320)	(0.377)	(0.066)	(0.081)	(0.282)	(0.57)	(0.087)	(0.081)
Child Age		-0.006		-0.001		0.011		0.000		0.009		0.1***
		(0.004)		(0.004)		(0.022)		(0.005)		(0.02)		(0.006)
Female Caregiver		0.024		0.033		0.4***		0.038		0.29**		0.040
		(0.034)		(0.031)		(0.151)		(0.035)		(0.12)		(0.036)
Caregiver Age		-0.000		-0.00**		-0.003		-0.001		-0.000		0.001
		(0.001)		(0.001)		(0.003)		(0.001)		(0.00)		(0.001)
Caregiver married/cohabiting		0.023		0.044		0.4***		0.044		0.24**		0.018
		(0.033)		(0.031)		(0.147)		(0.034)		(0.12)		(0.034)
Education: ref: No schooling												
Standard 1-8		0.015		0.012		0.086		0.030		0.084		-0.015
		(0.020)		(0.018)		(0.095)		(0.022)		(0.08)		(0.023)
Form 1 -6		0.003		0.016		0.077		0.018		0.032		0.019

	(0.029)	(0.025)	(0.145)	(0.031)	(0.11)	(0.035)
Above secondary	-0.003	0.021	0.388	0.062	0.231	0.067
	(0.058)	(0.053)	(0.243)	(0.056)	(0.19)	(0.063)
HH size	-0.007	0.001	-0.027	0.004	-0.010	-0.008
	(0.008)	(0.007)	(0.039)	(0.008)	(0.03)	(0.009)
Number of rooms	0.007	0.006	0.024	0.005	0.012	0.011
	(0.006)	(0.006)	(0.029)	(0.006)	(0.03)	(0.008)
Clinic fees	0.002	0.00**	0.001	0.00**	0.005	-0.003*
	(0.001)	(0.001)	(0.006)	(0.001)	(0.01)	(0.001)
Mobile clinic availability	0.017	0.008	0.041	0.016	0.084	0.025
	(0.018)	(0.016)	(0.082)	(0.02)	(0.06)	(0.021)
Medicine Availability	-0.04**	-0.04**	-0.140	-0.04**	-0.12*	0.004
	(0.020)	(0.018)	(0.089)	(0.020)	(0.07)	(0.024)
Distance to nearest health facility: ref: 0-2km						
2-5km	-0.011	-0.001	-0.126	0.004	-0.116	-0.05**
	(0.020)	(0.018)	(0.090)	(0.020)	(0.08)	(0.023)
5-10km	0.006	-0.009	-0.265*	-0.001	-0.22**	-0.1***
	(0.031)	(0.024)	(0.149)	(0.026)	(0.11)	(0.041)
>10km	-0.062	-0.069	-0.39**	-0.081*	-0.3**	-0.12**
	(0.042)	(0.042)	(0.159)	(0.043)	(0.15)	(0.048)
District: Ref: Garissa						
Homabay	0.014	0.039	0.51**	0.018	0.36**	-0.057
	(0.052)	(0.047)	(0.220)	(0.053)	(0.17)	(0.057)
Kisumu	0.11**	0.1***	0.9***	0.1***	0.7***	-0.078
	(0.049)	(0.044)	(0.198)	(0.047)	(0.15)	(0.048)
Kwale	0.1***	0.2***	1.3***	0.1***	1.1***	0.065
	(0.046)	(0.041)	(0.181)	(0.043)	(0.17)	(0.046)
Migori	0.054	0.070	0.48**	0.020	0.293*	-0.026
	(0.052)	(0.044)	(0.210)	(0.054)	(0.17)	(0.050)
Nairobi	0.2***	0.2***	1.2***	0.2***	0.9***	-0.031
	(0.046)	(0.042)	(0.201)	(0.045)	(0.15)	(0.049)
Suba	0.062	0.12***	0.670***	0.105**	0.60***	-0.015

Constant	0.853***	(0.051) 0.665***	0.887***	(0.044) 0.728***	3.06***	(0.205) 1.33**	0.873***	(0.047) 0.627***	2.881***	(0.160) 1.138*	0.889***	(0.051) 0.664***
	(0.037)	(0.114)	(0.033)	(0.095)	(0.182)	(0.538)	(0.037)	(0.127)	(0.162)	(0.592)	(0.049)	(0.102)
Observations	2,428	2,427	2,434	2,433	2,157	2,156	2,369	2,368	2,140	2,139	2,226	2,225
R-squared	0.008	0.048	0.008	0.050	0.008	0.089	0.010	0.059	0.011	0.082	0.011	0.138
Total impact – High risk preference	-0.035	-0.021	-0.017	-0.009	-0.096	-0.135	0.003	0.007	-0.052	-0.098	0.039	0.017
	(0.038)	(0.53)	(0.035)	(0.050)	(0.187)	(0.234)	(0.041)	(0.057)	(0.167)	(0.18)	(0.053)	(0.057)
Total impact – Low risk preference	-0.062	-0.079	-0.054	-0.062	-0.181	-0.191	-0.025	-0.031	0.48**	0.458	0.121*	0.106*
	(0.052)	(0.069)	(0.047)	(0.058)	(0.253)	(0.293)	(0.052)	(0.060)	(0.223)	(0.54)	(0.068)	(0.057)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0; #program impact is the sum of the difference-in-difference estimate and the triple-difference estimate; Program impacts estimated using the lincolm command.

3.3.4. Sensitivity analysis

We find that our results are sensitive to classification of our outcomes (Appendix B3.1). Specifically, when we rerun sperate analysis for measures created from the health card and from the self-reported measures we do not find any significant moderating effects on any of the outcomes. However, this could be due to the reduction in sample size when stratify the analysis by source of outcome data. We also do not observe any moderating effect when we classify risk and time preference as a continuous measure (Appendix B3.2). However, this is unsurprising as we used a stricter economic preference measure for our main analysis. Nonetheless, our main findings remain consistent when we run weighted regression models using inverse probability weights (Appendix B3.3).

3.4. Discussion

Our study analyzed the moderating effect of time and risk preference on cash transfer program impacts on child healthcare utilization. We found evidence that a caregiver's time preference but not risk preference moderates the impact of the CT-OVC on child healthcare utilization. Specifically, we found that children who lived in a household that received the CT-OVC and had a caregiver with a low discount rate were more likely to have a health card, and receive a BCG, polio and DPT vaccination. These children also received a higher number of polio vaccinations on average. These findings contribute to the literature on cash transfer impact evaluations by providing evidence that the time preference of a recipient may affect healthcare service use for their children.

Consistent with previous studies,[15,74,75] when we assessed the CT-OVC impact without accounting for economic preferences, we did not find any significant effect for any of our measures

of child healthcare utilization. The CT-OVC is an unconditional cash transfer program, and as such, receipt of the cash transfer was not conditional on taking a child to receive healthcare services for instance. It has been purported that unconditional cash transfer programs may not improve child healthcare service use.[73] However, our study finds that the CT-OVC, despite being unconditional, may in fact improve child healthcare utilization when we account for caregiver time preference. This finding is consistent with evidence from Latin America on the effectiveness of cash transfer programs on healthcare utilization.[101,102]

Our main finding that time discounting moderates cash transfer impacts on child healthcare utilization is consistent with evidence from existing literature showing increased healthcare use amongst individuals with low discount rates.[80,81] Individuals face a choice of spending their money and time on current healthcare utilization that has some future benefit or using their money and time in the present for other goods and services that have smaller more immediate benefits. We show that caregivers who place a higher value on future benefits have a higher likelihood of taking their children to receive vaccinations when they receive a cash transfer. This implies that the cash transfer enabled caregivers with low discount rate to increase child healthcare utilization.

While our study found some evidence of a moderating effect of time preference on child healthcare utilization, we note that this effect was significant for most of our measures related to child vaccinations (BCG, Polio and DPT vaccinations). Similar to another study in Kenya, the vaccinations rates in our sample were relatively high at baseline in 2007 (>82%),[103] this implies that overall, surveyed participants in these areas already placed a high value on getting vaccinations. Although, full vaccination coverage and timely receipt of the vaccinations is an ongoing problem in Kenya.[103] However, we also found a significant moderating effect on having a health card. Having a health card is as an important indicator of child healthcare utilization as a

health card is usually provided at a child's birth or during a visit to a healthcare facility.[90] This finding on our measure for having a health card therefore reinforces our finding that time preference moderates healthcare use as having a health card suggests an encounter with a healthcare facility. Further, it could be the case that these visits to a healthcare facility increase the likelihood of being informed about the importance of child vaccinations and could explain our observed effects on vaccination receipt.

Nonetheless, we do not find any evidence that risk aversion moderates cash transfer program effects despite evidence that risk aversion is associated with healthcare use.[85–87] Amongst these studies, only one was conducted in a sub-Saharan African country, Nigeria. In this study, participants who were risk averse had a higher likelihood of accepting a malaria rapid diagnostic test.[87] It is possible that the deviation of our finding is due to differences in the study samples. Specifically, with this study conducted in Nigeria, the choice of testing for Malaria was amongst individuals who had just purchased mosquito net for themselves. This sample already included individuals who had high health seeking behaviors. Further, despite the evidence that risk preference is associated with healthcare use, these studies are not directly comparable to ours as they explored a direct relationship of preferences and healthcare use. Our study is the first to explore the relationship between economic preferences, cash transfers and healthcare use.

3.4.1. Limitations

Our study has three important limitations. Firstly, the outcomes used in the analysis are a combination of data obtained from the health card and self-reported measures, and the latter are more likely to be reported with bias.[103] We addressed this limitation by conducting a sensitivity analysis using measures that were collected from the health card only and those that were self-

reported. Secondly, economic preferences were only collected during the last wave of the CT-OVC evaluation in 2011. There is evidence suggesting that the CT-OVC had no effect on these economic preferences measures which may be explained by the low cash-transfer amount in relation to household consumption.[91] In addition, caregivers in our sample were mainly older and may not experience a huge shift in preferences over a short time period.[81] We therefore assumed preferences did not vary significantly during our analytical time period. Nonetheless, we still used a conservative measure of time discounting and risk aversion such that it is unlikely that a caregiver's preferences will change significantly if they have the lowest discount rate or highest risk aversion. Regardless, the estimates from the triple-difference model may suggest that this assumption is violated. This is due to the estimated differences in probabilities between different groups. For instance, the difference in the average outcomes for children with a low discount rate in the post period compared to those children with a high discount rate in the baseline period. Although it is likely that the economic preference variables are endogenous, the same preference variables are used in the baseline and post period and are not changing in the analysis. We are unable to test our assumption that preferences do not change with the available data.

Thirdly, due to the small sample size, running the triple-difference model creates interactions with very small samples that are leading to counterintuitive estimates from the triple-difference model. An example of the counterintuitive finding is in Table 9 (unadjusted model) where it is implausible that children with patient caregivers have a 0.283 higher probability of having health card among control group but have a lower probability among CT-OVC group. As shown in the Appendix B4, the number of children in the baseline period that did not receive the cash transfer and had a low discount rate is a small sample size (n=17) yet the probability of having them healthcare card is the highest 0.82. This is the pattern with all the outcomes (receiving a

BCG, polio or flu vaccination). The conservative measure we use for time preference plays a huge role in reducing this sample size. Although we use an alternative specification for the time preference models, our choice of measurement of time preference follows prior literature.[91] Further, there is the possibility of spillover effects of the cash transfer to non-cash transfer households that may be influencing the counterintuitive findings of the triple-difference model as prior studies assessing a similar cash transfer in Lesotho has shown positive spillovers to non-cash transfer benefeciaries.[104] Future studies could replicate this study on a lager dataset, and offer a comparison of estimates, as this study provides initial evidence to support the moderating effect of time preferences on the impact of cash transfers on child healthcare use. Despite these limitations, our study is the first to our knowledge to provide evidence on the moderating effect of economic preferences on cash transfer program impacts on child healthcare utilization.

As this study underscores the role of economic preferences in healthcare decisions, implementing "cash plus" programming, that is, providing the cash transfer with complementary support, may address the role preferences have in dampening the intended program effects. Cash plus programs are recommended as the income effect from standard cash transfer programs may not be large enough to achieve the desired outcomes.[105] Cash-plus programs have been successful as evidenced by the success of the LEAP (2000) implemented in Ghana where universal health insurance coverage was the complementary program. As we find that cash transfer effects differ by time preference, the complementary program can include information and behavior change communication to target caregivers that may have high discount rates. This complementary program could be designed using a behavioral economic policy tool, framing. Framing would involve presenting information about the choice on whether or not to utilize child healthcare services, by additionally presenting the information around the other choices that surround it, such

that utilizing child health services is a better option in comparison.[83] In addition to targeted communication to improve the use of preventative healthcare services, the cash plus program can be designed to improve nutrition outcomes for children such as in Ethiopia where an integrated nutrition social cash transfer program was implemented.[105]

3.4.2. Conclusion

Children in developing countries suffer high rates of preventable and treatable illnesses which can be addressed with regular healthcare use. There is debate on whether cash transfer programs should be implemented, in part, due to the mixed evidence that exists. Prior studies that have examined cash transfer program impacts do not account for the role economic preferences in moderating program impacts.[13,15,66,74,75,77] We showed that understanding whether economic preferences are a modifier in the relationship between cash transfers and healthcare allows for a more comprehensive evaluation of cash transfer program effects. This study is the first to provide evidence that the CT-OVC program improves child healthcare utilization measures (having a health card and receipt of vaccinations) and this effect is moderated by time discounting. Investment into cash transfer programs should be supported as they improve children's health. In addition, prior evidence such as from the evaluation of the Ghana Livelihood Empowerment Against Poverty (LEAP) 2000 program found improved social support for beneficiaries.[106] This means that expanding cash transfer programs can improve the target beneficiaries beyond the cash benefit from the program. An important implication of this finding is that cash transfers to individuals with high discount rates are likely to be ineffective in improving the use of healthcare services for children.

Chapter IV: Are cash transfer programs cost-effective in reducing infectious diseases amongst orphans and vulnerable children in Kenya?

4.1. Introduction

In Kenya, approximately 74,000 children die before reaching their fifth birthday every year.[107] Most deaths amongst children are from preventable and treatable diseases such as malaria and pneumonia which account for two-thirds of child deaths in developing countries.[15,108,109] It is estimated that over 75% of the population is at risk of malarial infection causing about 20% of all under-five deaths.[15] Further, acute respiratory infections cause about 16% of child deaths in Kenya.[15] As both malaria and respiratory infections are preventable and treatable with access to and utilization of recommended healthcare services,[110,111] recent policies have attempted to address the problem of child mortality through providing a cash transfer to low-income populations.[15,112–114] Providing unconditional cash transfers to low-income households can address barriers to health care access and health production, such as transport and hunger,[14,112] to reduce diseases and mortality amongst children.[115]

In 2007, Kenya's largest social protection program, the Cash Transfer for Orphans and Vulnerable Children (CT-OVC) program was rolled out by the Ministry of Gender, Children and Social Development.[65] The CT-OVC was rolled out as a pilot program costing approximately US$ 10 million. The CT-OVC has been scaled-up and included in the governments national budget allocating approximately US$85 million to over 310,000 households in 2013-2014.[116] The objective of the CT-OVC was to promote human capital development through improving children's health.[66] The program gave approximately Ksh 344 (US$4.34; 2010) per adult equivalent a month to households with a child whose main caregiver was chronically ill or deceased.[65,66]

A longitudinal cluster-randomized study was designed to evaluate the impact of the CT-OVC program on children's health.[15,66] Using the evaluation data, a recent study found that the CT-OVC program was effective in decreasing infectious diseases (malaria and pneumonia) among children under seven years.[15] Specifically, the study found that children that lived in households that did not receive the cash transfer had 1.8 higher odds of being ill compared to children who lived in a household that received the transfer.[15] Other studies have additionally found that cash transfer programs are effective in improving children's health. For instance, in a systematic review and meta-analysis, cash transfers were effective in improving children's nutrition outcomes.[117] In Latin America, conditional cash transfers have been found to be effective in improving health outcomes such as reducing morbidity risk, and improving nutritional outcomes, health service use and immunization coverage.[101,102] While the CT-OVC, and other cash transfer programs, are effective in improving child health, it is unknown whether cash-transfer programs are cost-effective in reducing infectious diseases amongst children.

We conducted an incremental cost-effectiveness analysis of the CT-OVC in reducing malaria and pneumonia amongst children under the age of seven. The objectives of this research are twofold. Firstly, we examined the economic costs (that is, medical, non-medical and productivity loss) associated with the CT-OVC program compared to the status quo. We hypothesized that the cost of the CT-OVC is higher than the status quo (i.e., children in households that were eligible to receive the cash transfer but did not) because of high administrative cost to implement the cash transfer program and cash transfer payments of the CT-OVC. Secondly, we assessed the incremental cost-effectiveness of the CT-OVC in reducing illness amongst children that received the cash transfer compared to the status-quo. We hypothesize that providing the cash

transfer to households with children under the age of seven years is cost-effective in reducing infectious diseases compared to the status quo based on prior evidence of effectiveness. [15,16]

4.1.1. Overview of the CT-OVC program

The CT-OVC program was a collaboration between the Government of Kenya's Department of Children's Services (DCS), with financial assistance from the United Nations Children's Fund (UNICEF) and the Department for International Development (DFID).[15] It was introduced as a pre-pilot during 2004 and expanded to include over 240,000 households as of 2014.[15] The objective of the program was to provide a social protection system through regular and predictable cash transfers to families so as to promote the human capital development of orphans and vulnerable (OVC) children.[66] Specifically related to child health, the program was intended to reduce child mortality and morbidity through increased uptake of immunizations, growth control and vitamin A supplements.[66] A household was eligible for the cash transfer if it had a child under the age of 18 and a deceased or chronically ill child parent (or caregiver), was poor and was not receiving any other assistance.[15] While entry into the program is unconditional, recipients are informed that the purpose of the cash transfer is to support the care of children through investing in human capital.[15]

4.1.2. Prior studies conducting economic evaluations of cash transfer programs

Cash transfer programs play an important role in alleviating vulnerable populations from extreme poverty, and are effective in improving child health,[15,113,114,118] yet, there is limited evidence on their cost-effectiveness,[119] particularly in sub-Saharan Africa. A review of the existing literature on economic evaluations of cash transfer programs in sub-Saharan Africa, as well as

studies in the region assessing programs to reduce malaria and pneumonia among children, show that while there are some economic evaluation studies, there are limited formal cost-effectiveness studies.

Regarding economic evaluations of cash transfer programs, in a study comparing the cost-effectiveness of a cash transfer and food transfer program in Malawi,[120] found the cash transfer program cost beneficial (based on the cost per program beneficiary) in improving food security compared to the food transfer program. Another study assessing a mobile cash transfer program to prevent child undernutrition in Burkina Faso found the program had a higher cost per beneficiary compared to other programs.[121] Further, in a meta-analyses of cash transfer programs and educational impacts, the authors found considerable heterogeneity in cost-effectiveness amongst nine cash transfer programs analyzed.[122] In this study, the authors assessed cost-transfer ratios (i.e., the ratio of non-transfer costs to the value of money actually transferred to the beneficiary). As this differs from a cost-effectiveness analysis,[123,124] this study addresses the gap in knowledge by conducting an incremental cost-effectiveness analysis of a cash transfer program with regard to child health.

There have been studies evaluating the cost-effectiveness of various approaches to prevent malaria in children in Kenya.[125–127] One study found that delivering intermittent preventive treatment through teachers was a cost-effective strategy in preventing malaria in children.[125] Although, the alternative strategy was not clearly defined in the study. Another study that modelled the cost-effectiveness of malaria control interventions found that employing long lasting insecticide treated nets (ITN) was highly-cost effective in reducing disability-adjusted life years (DALYs) over a five year period.[126] A related study found ITN highly cost effective in averting deaths among children in Kenya.[127] Other studies have been conducted in sub-Saharan

Africa.[128,129] For instance, one study found that pre-referral treatments using community health workers was cost-effective in averting DALYs in children compared to provision using a health facility.[128] However, there are no studies that have examined the cost-effectiveness of a cash-transfer program in reducing malaria amongst children.

Regarding economic evaluations of programs to prevent pneumonia among children, a cost-effectiveness analysis on vaccines against pneumonia was conducted in Kenya.[130] The study found that vaccinations were cost-effective in preventing pneumonia compared to no vaccinations from the societal perspective.[130] Another study that examined data from 72 countries including Kenya found vaccinations as a cost-effective strategy to prevent child mortality.[131] Other studies analyzing cost-effectiveness of strategies to prevent pneumonia in children have been conducted in Malawi[132] and South America.[133–135] As most of these studies examined the cost-effectiveness of vaccination strategies[133–135] and only one cross-country analysis examined environment and nutritional strategies,[136] a critical gap exists in the literature on cost-effectiveness of a cash transfer program as a strategy for the prevention of illness in children. This study fills the gap in the literature and provides evidence on the cost-effectiveness of a cash transfer program in reducing malaria and pneumonia in children in Kenya.

4.2. Methods

We conducted an incremental cost-effectiveness analysis of the CT-OVC program in reducing infectious diseases amongst children that received the cash transfer compared to the status quo. This study used data from a longitudinal cluster-randomized study evaluating the CT-OVC (2007 and 2009),[137] the grey literature[66] and peer-reviewed literature.[16,138,139] Outcome data were

obtained from the CT-OVC program evaluation data and costs were from the grey literature and peer-reviewed literature.

We conducted the cost-effectiveness analysis from the payer or healthcare and societal perspective. As this was a national-level program that has potential to be scaled up by government and cooperating partners, it becomes important to provide evidence to the payers (governments and non-government funders) on whether the program is cost-effective. The societal perspective is analyzed as this encompasses the costs associated with the payer and the patient which vary by the two treatment groups. We conducted the analysis from the societal perspective as there are patient costs associated with the alternative strategies. Further, it is recommended that the societal perspective be included in cost-effectiveness analysis.[123,124] We compared the incremental costs and incremental effectiveness of receiving the CT-OVC (i.e., children in households that were eligible and received the cash transfer) compared to the status quo (i.e., children in households that were eligible to receive the cash transfer but did not).[15] We conducted the analysis over a two-year time horizon, which is the time between baseline and follow-up of the longitudinal cluster-randomized study evaluating the CT-OVC.

4.2.1. Overview of the longitudinal cluster-randomized study design

The CT-OVC begun as a pilot study in 2004. Prior to its expansion in 2007, UNICIEF and Oxford Policy Management designed a longitudinal cluster-randomized study to track the impact of the program.[66] The study involved conducting a baseline household survey before the cash transfer program could be expanded and conducting a follow-up survey after 24-months (2009) and 48-months (2011).[89] The DCS identified seven districts across the country that were scheduled for inclusion in the expansion of the CT-OVC program.[66] In the selected districts, four locations

were selected as eligible. Of these four locations, two were randomized to the initial expansion and the others would serve as the control locations.[66] Due to financial constraints, the CT-OVC expansion program could not be rolled out to all eligible locations at the same time.[66] The evaluation of the CT-OVC program was therefore designed as the location of those whose entry would occur later to be the control group.[66]

In the intervention locations, targeting of the households was conducted based on the standard program operation guidelines.[66] This includes formation of a committee of individuals in each community that identify households based on poverty indicators and having an OVC.[15] The list of households identified by the committee are then sent to the Ministry of Gender, Children and Social Development Community. The Ministry then confirms eligibility using a questionnaire to rank households. This reduces the selection bias of households into the program as the CT-OVC recipients are selected at the district-level.[15] In the control locations, program targeting was simulated in order to identify a sample of households that were comparable to those identified as eligible in the treatment groups.[66] Both the treatment and control households were interviewed before the roll-out of the expansion program in 2007 and prior to knowledge that they were selected into the program.[66] They were then interviewed again after the expansion of the CT-OVC program to the treatment group in 2010. The data collected from these surveys informed the evaluation of the CT-OVC program.

4.2.2. Sample

We retain all children in the sample from the baseline survey (n=2593). There were 1588 children in the treatment group (received the cash transfer) and 1005 children in the control group (status quo). 739 of these were in wave 1 and not wave 2 and were lost to follow-up. As malaria

and pneumonia in children may cause mortality, we accounted for the possibility that the children in the baseline survey and not in the follow-up could have died. We assumed that some of these children could have died from a case of malaria based on the illness-specific age-sex mortality.[140] We randomly assigned children based on a draw from a uniform distribution, such that we had 127 children who experienced either malaria or pneumonia and were assigned as dead. We used t-tests and found no statistically significant differences in the demographic characteristics of children in the treatment compared to those in the control groups for the study sample.

4.2.3. Effectiveness

The study measures whether a child aged less than seven years had a case of either malaria or pneumonia (i.e., 1 = malaria or pneumonia). Measures for malaria and pneumonia are self-reported symptoms observed by the caregivers of the household who were asked whether the child had been ill with fever, hot body, or cough at any time in the last month. Following a prior study,[15] we report the effectiveness using the odds ratio..

We replicated the analysis of a prior study[15] to verify that the CT-OVC is effective in reducing illnesses amongst children. The replication results are reported in Appendix C1. We obtained an odds ratio of 0.535 (95% CI 0.336-0.851) compared to the odds ratio of 0.556 reported in the prior study. The difference in odds ratio may be attributed to differences in estimation packages and stata commands that the authors may have used. However, for reasons discussed in Appendix C5, we use the GEE model to estimate our incremental effectiveness.

4.2.4. Incremental effectiveness

We empirically defined the incremental effectiveness of the CT-OVC using disability-adjusted life years (DALY) averted similar to several studies on child health[141–144] and as recommended by the World Health Organization (WHO) guide for cost-effectiveness.[123] The advantage of using DALYs as the measure of incremental effectiveness is the comparability of this measure to other studies assessing the impact of different strategies on malaria and pneumonia.[141,142,144] Further, as malaria and pneumonia are responsible for the high rates of child mortality in Kenya,[15] the DALYs take into account the years of life lost as well as the morbidity of a child due to the illness.[123] DALYS are calculated using the following equation:

$$DALY = YLL + YLD \quad \text{(i)}$$

Where *YLL* is the years of life lost due to premature mortality and YLD are the years lived with disability[123]. Following the global burden of disease, the YLL that includes both age-weighting and discounting is given by the following equation:

$$YLL = \frac{KCe^{ra}}{(r+B)^2}\left[e^{-(r+B)(L+a)}[-(r+B)(L+a)-1] - e^{-(r+B)a}[-(r+B)a-1]\right] + \frac{1-K}{r}(1 - e^{-rL}) \quad \text{(ii)}$$

Where a is the age of death (years), r is the discount rate, *B* is the age weighting constant, *K* is the age-weighting modulation constant, *C* is the adjustment for age-weights and *L* is the standard life-expectancy. The *YLD* with age-weighting and discounting is given by the following equation:

$$YLD = DW\{\frac{KCe^{ra}}{(r+B)^2}\left[e^{-(r+B)(L+a)}[-(r+B)(L+a)-1] - e^{-(r+B)a}[-(r+B)a-1]\right] + \frac{1-K}{r}(1 - e^{-rL})\} \quad \text{(iii)}$$

Where a is the age of death (years), r is the discount rate, *B* is the age weighting constant, *K* is the age-weighting modulation constant, *C* is the adjustment for age-weights, *L* is the duration of the disability and *DW* is the disability weight. However, we did not conduct age-weighting as we found no differences in demographic characteristics between treatment and control and did not anticipate that this will impact the incremental effectiveness. Although several approaches exist in implementing the DALY's[145] we use the approach as presented by the global burden of disease by the WHO,[146] and as commonly used in prior literature.[141,144]

Therefore, the YLL in this study only apply discounting using the reduced equations as follows:

$$YLL = \frac{N}{r}(1 - e^{-rL}) \quad \text{(iv)}$$

Where *N* is the number of deaths, *L* is the standard life expectancy at death and r is the discount rate. We apply the age-sex-specific life expectancy for 2010 (the closest year available for our analytical period) from the WHO[147] as follows: male aged 0-4 years as 60.87, male aged 5-7 as 58.07, female aged 0-4 years as 64.36 and female aged 5-7 as 61.55. We apply a discount rate of 3% as recommended.[123]

The YLD was implemented in the study as follows:

$$YLD = \frac{I\ x\ DWx\ L(1-e^{-rL})}{r} \quad \text{(v)}$$

Where *I* is the number of incident cases, *DW* is the disability weight, *L* is the duration of the illness and *r* is the discount rate. The disability weight associated with malaria is 0.20 and that of an episode of pneumonia 0.28.[146] An onset of malaria lasts for an average of 7 days (or 0.019 years),[141] while that of pneumonia lasts for 5 weeks (or 0.096 years) on average.[148] We use the recommended discounting rate of 3%.[123]

We separately calculated the total DALYs associated with malaria (3441 DALYs) and that of pneumonia (3163 DALYs) for our sample. The calculation of DALYs is provided in Table 13 and Table 14. We then calculated the average DALY associated with a case of malaria (2.46 DALYs per case of malaria) and a case of pneumonia (2.19 DALYs per case of pneumonia). We assign the associated DALYs for a child that had either malaria or pneumonia. However, for a child that experienced both malaria and pneumonia we added the associated DALYs to obtain the total DALYS for an illness. The difference in DALYs between treatment and control is the DALYs averted or the incremental effectiveness. We estimated a generalized estimating equation (GEE) to calculate the incremental effectiveness.

Table 13: Disability Adjusted Life Year (DALY) calculation for Malaria

	Population	Incidence	Incidence/ Population	Age at onset	Duration	DW	YLDs
YLD - Year 1							
Males:							
0-4	613	316	0.515	1.980	0.019	0.2	0.0007
5-7	590	137	0.232	5.820	0.019	0.2	0.0003
Females:							
0-4	725	362	0.499	2.017	0.019	0.2	0.0008
5-7	665	84	0.126	5.607	0.019	0.2	0.0002
YLD - Year 2							
Males:							
0-4	314	156	0.497	2.720	0.019	0.2	0.0003
5-7	190	84	0.442	5.840	0.019	0.2	0.0002
Females							
0-4	394	172	0.437	1.660	0.019	0.2	0.0004
5-7	209	89	0.426	5.840	0.019	0.2	0.0002

	Population	Deaths	Death/ Population	Average age at death	Standard LE	YLL
YLL						
Males						
0-4	613	34	0.055	2.120	60.87	950.8209
5-7	590	28	0.047	5.570	58.07	769.8580
Females						
0-4	725	30	0.041	1.930	64.36	854.9679
5-7	665	22	0.033	5.450	61.55	617.6218

DALYs	**Male**		**Female**		**Total**	
	Cases in 2 years	**DALYS**	**Cases in 2 years**	**DALYs**	**Cases in 2 years**	**DALYs**
0-4	472	950.822	534	950.822	1006	1901.644

5-7	221	769.858	173	769.858	394	1539.717
Total	693	1720.680	707	1720.680	1400	3441.361
DALY/case		2.483		2.434		**2.458**

Table 14: Disability Adjusted Life Year (DALY) calculation for pneumonia

	Population	Incidence	Incidence/ Population	Age at onset	Duration	DW	YLDs
YLD Year 1							
Males:							
0-4	613	318	0.519	2.142	0.096	0.280	0.025
5-7	590	134	0.227	5.843	0.096	0.280	0.010
Females:							
0-4	725	372	0.513	2.032	0.096	0.280	0.029
5-7	665	92	0.138	5.554	0.096	0.280	0.007
YLD Year 2							
Males:							
0-4	314	153	0.487	2.667	0.096	0.280	0.012
5-7	190	90	0.474	5.800	0.096	0.280	0.007
Females:							
0-4	394	188	0.477	2.660	0.096	0.280	0.015
5-7	209	100	0.478	5.900	0.096	0.280	0.008

	Population	Deaths	Death/Population	Average Age at death	Standard LE	YLL
YLL						
Males:						
0-4	613	31	0.051	2.120	60.870	866.925
5-7	590	26	0.044	5.620	58.070	714.868
Females:						
0-4	725	27	0.037	1.810	64.360	769.471
5-7	665	28	0.042	5.360	61.550	786.064

DALYs						
	Male		**Female**		**Total**	
	Cases in 2 years	**DALYS**	**Cases in 2 years**	**DALYs**	**#Cases in 2 years**	**DALYs**

0-4	471	866.961	560	866.968	1031	1733.929
5-7	224	714.885	192	714.883	416	1429.769
Total	695	1582	752	1582	1447	3163.698
DALY/case		2.276		2.104		**2.186**

4.2.5. Economic costs

The baseline economic costs were obtained from the grey and peer reviewed literature. The costs were classified as either fixed costs (do not vary with output in the short term, such as facility costs) or variable costs (vary with output, such medications). We assigned the costs based on both a micro-costing and gross costing approach. Table 15 shows that the baseline costs vary by treatment group. We estimated the economic costs for the treatment and control group by multiplying the resource used by each child by the unit cost of the resource. The sections that follow describe the cost source including the search strategy, cost reporting and cost assignment in more detail (section a, b and c, respectively).

Table 15: Baseline cost components vary by treatment group

COST COMPONENTS	**CT-OVC**	**Status-quo**
Payer perspective:		
Cash transfer value	x	
Drugs for case of Malaria	x	x
Nurses for treatment of Malaria	x	x
Drugs for case of Pneumonia	x	x
Nurses for treatment of Pneumonia	x	x
Overhead	x	x
Health facility	x	x
Cash transfer administration	x	
*Societal perspective:		
Transport for receipt of cash transfer	x	
Transport to clinic	x	x
Average wage (opportunity cost of time – receipt of cash)	x	
Average wage (opportunity cost of time – care for ill child)	x	x

* Includes payer perspective

a. Cost sources:

As the longitudinal cluster-randomized study evaluating the CT-OVC was not designed to conduct an economic evaluation, costs were collected from grey literature and peer-reviewed literature. Cost data on the cash transfer amount and administrative costs were obtained from the grey literature were obtained from UNICEF[66] and the WHO Choosing Interventions that are Cost-Effective project (or WHO-CHOICE).[149] A costing study on the CT-OVC is available from UNICEF that informed the costs associated with the implementation of the CT-OVC program. All other costs were obtained from peer-reviewed literature.[126,150–153] For the peer-reviewed literature, we prioritize studies conducted in Kenya searching databases PubMed and Google Scholar using specific search terms. The search terms in Pubmed and google scholar included the following combinations: "malaria" OR "pneumonia" AND "cost" OR "economic burden" OR "cost-effectiveness" OR "economic evaluation" OR "cost-benefit" AND "Kenya" OR "sub-Saharan". Where studies from Kenya are not available, we prioritized studies from countries with similar context to Kenya based on region, gross domestic product (GDP) per capita and year the study was conducted. Region will be prioritized based on East African countries then sub-Saharan countries. GDP per capita will be obtained from the World Bank and studies conducted closest to the time the CT-OVC was implemented will be prioritized. The table below provides the baseline costs and sources:

Table 16: Baseline costs, in US$ 2018

Cost component	Unit of measurement	Base case	Lower bound	Upper bound	Reference
CT-OVC					
Cash transfer payment	Per month	5.96	2.98	8.94	[66]
Administration	Per household per year	271.01	135.50	406.51	[66]
Medications					
Malaria Medication	Per tablet	0.52	0.36	0.68	[126]
Drugs for case of Pneumonia	Per case	0.29	0.14	0.43	[150]
Nurse Salary	Per month	0.14	0.04		[151]
Health facility	Per day	21.83	6.58	0.24	[149]
Patient costs				37.08	
Collection of cash transfer (Garissa district only)	Per month	1.20	0.60		[66]
Collection of cash transfer (all districts except Garissa)	Per month	1.16	0.58	1.81	[66]
Transport to visit a clinic	Per visit	0.17	0.09	1.74	[152]
Care giver time	Per day	3.36	1.68	0.26	[153]

Where confidence intervals were not provided, we use 50% higher and lower than the base case as the upper and lower bound, respectively.

b. Cost reporting:

We report the costs in United States dollars (US$) as this is the most commonly reported and easily understood currency in the world that has the advantage of being easily converted to other currencies because of its wide use.[154] For instance, we assume it is highly likely for a Kenyan policy maker to understand and easily convert US$ to Kenyan shillings. This is also relevant for donors or cooperating partners who may fund the cash transfer program and fund programs in US$; noting that donor funds are also usually reported in US$.[154] We use the exchange rate from the World Bank to convert to US$ after adjusting for inflation. We discuss the advantages and disadvantages of using other currency for reporting in detail in Appendix C2.

We adjusted for inflation and report the costs in constant 2018US$. Since the cluster-randomized study was conducted for more than a year and cost sources came from multiple time

periods, we inflation adjust the costs to account for the differences in purchasing power at different times and convert them to a common time period.[155] To adjust for inflation, we used the GDP deflator accessible from the World Bank.[156] Although it is recommended to inflation adjust to the year in which the results will be reported,[155] we inflation adjust costs to 2018 as this is the most recent year where the GDP deflator from the World Bank is available.[156] We adjusted for inflation before applying the exchange rate. Inflation adjusting approaches are compared and discussed in Appendix C2. As the cluster-randomized trial was conducted for more than a year, we discount costs so that all costs reflect the present value. Discounting is the process of converting future cost to their present value.[123] This is important for economic policy to allow policy makers to compare costs overtime. We use a rate of 3% per year.

c. Cost assignment:

Costs were assigned based on both micro-costing and gross costing. Micro-costing entails conducting a detailed measurement of all activity inputs to determine costs.[157] The costs were assigned to each child based on whether they were in the treatment group, their treatment needs and the number of children in the household. This entails multiplying the unit cost by each child. Gross costing is also used as there are costs that cannot be assigned at the child level. Therefore, aggregated data will be used to determine the average cost per child. The cost assignment details are described below:

i. Cash transfer costs: We obtained the total cost of the cash transfer program and averaged this cost per households that were targeted in the CT-OVC program. We only assigned this average at the household level as there is no evidence that the cost of the cash transfer is based on the number of children in the treatment household.

ii. Medications: We included the average costs of treatment drugs for pneumonia and malaria. To assign the cost of medication we multiplied the unit cost of the drug by the number of days it takes to treat the illness in a child. We assumed that an illness requires a seven-day treatment.[153]

iii. Labor costs: We used the average salary of a nurse and assigned the cost based on the number of times a child is taken to the clinic when they have an illness. We assumed that an ill child required two clinic visits; one at the beginning of the treatment and one to review the condition of the child. We also assumed it takes 20 minutes to care for an ill child.[125]

iv. Health facility costs: We used gross costing to determine the health facility cost as actual utilization of the resources for each child cannot be determined. We assumed a visit lasts for approximately 20 minutes[125] and use this to determine the proportion of the monthly health facility cost that is assigned to each visit to the clinic.

v. Patient costs: We included patient costs in the form of transport costs and the opportunity cost of time spent caring for an ill child and for collecting the cash transfer. Since the cash transfer is administered monthly, the transport costs for receipt of cash transfer will be assigned as one trip a month for every child that is in the treatment group. We assumed that it costs a caregiver 4.5 income days to care for an ill child. Although it is common to use the minimum wage as a measure of productivity cost, for rural households that focus on a subsistence economy this may not be meaningful. We use an estimate of US$1 (2005 reporting year) a day based on a study that assessed the cost of uncomplicated fevers to households.

Table 15 shows the variation in cost-assignment by treatment groups.

4.2.6. Incremental cost

The incremental cost was calculated as the difference in costs between the treatment and control groups. We estimated a generalized estimating equation (GEE) to calculate the incremental cost.

4.2.7. Statistical Analysis

We estimated a generalized estimating equation (GEE) to estimate the incremental effectiveness (DALYs averted) and the incremental costs (US$2018). The GEE model with a binomial distribution and logit link was used to estimate the incremental effectiveness (DALYs averted) of the CT-OVC program. We used the GEE model because it estimates the change in the population mean given changes in the covariates while accounting for within neighborhood dependence.[158] We estimate the model of the form:

$$E(Y_{ij}) = \beta_0 + \beta_1 CTOVC_{ij} + \beta_2 Year_{ij} + \beta_3 (CTOVC_{ij} * Year_{ij)} + aX_{ij} \quad \text{(vi)}$$

Where *Y* is a binary measure for illness of the i*th* child from the *jth* community; CTOVC is 1 if the child was in a household that was a recipient of CT-OVC, and X is a matrix of participant characteristics (i.e. age, gender, education, orphan status, relationship to household head, wealth index, food insecurity, use of mosquito net, food variety, crowding index, unprotected water source and rural area: variable defined in Appendix C3) following the study that assessed the effectiveness of the CT-OVC.[15] The coefficient β_3 represents the effectiveness of the CT-OVC. We provide an evaluation of alternative statistical models in Appendix C4.

To estimate the incremental costs, we use the GEE model with a gamma distribution. We estimate the following equation:

$$E(Cost_{ij}) = \beta_0 + \beta_1 CTOVC_{ij} + aX_{ij} \text{ (vii)}$$

Where the Cost of the i*th* child from the *jth* community is a function of the CTOVC (equal to 1 if the child was in a household with CT-OVC) and X (the matrix of covariates as specified in model (vi) and Appendix C3). The coefficient of interest is β_1. We discuss the statistical models to estimate the costs and the rationale for selecting the GEE model in Appendix C5.

4.2.8. Cost effectiveness - Incremental Cost-effectiveness Ratio (ICER)

Cost-effectiveness was measured using the incremental cost-effectiveness ratio (ICER). The ICER is calculated as the incremental cost divided by the incremental effectiveness so that the ratio represents the cost (US$2018) per DALYS averted:

$$ICER = \frac{Incremental\ Cost}{Incremental\ Effectiveness} \quad \text{(viii)}$$

The threshold for cost-effectiveness was based on the Kenya's per-capita GDP (US$1,710.51; 2018) based on WHO guidelines,[123] such that the CT-OVC will be considered cost effective if it is less than 3 times Kenya's GDP per capita (i.e., <US$5,131.53.[159] As there is debate about the threshold for cost-effectiveness of 3 times the GDP per capita being too high and not in alignment with funded programs and policies, we additionally considered the CT-OVC as highly cost-effective if it is less than the per GDP/capita of Kenya (i.e., <US$1,710.51).[159] The threshold represents the willingness to pay for an additional child health benefit (or DALY averted) from the CT-OVC. To estimate the 95% confidence intervals of the ICER, we used non-parametric bootstrap using 1500 replications.[160] Although there is no consensus on the number of replications, it is recommended to have more than 1000 replications.[161,162]

4.2.9. Uncertainty analysis

a. One--way sensitivity analysis:

We assessed the uncertainty associated with costs obtained from different data sources. We conducted one-way sensitivity analyses, which are a deterministic sensitivity analysis where single cost components are varied and the effect on the ICER results is reported.[163] The deterministic analysis, although not commonly conducted in cost-effectiveness analysis, was used to provide more information on key factors driving the cost-effectiveness of the intervention. The one-way-sensitivity analysis was conducted by varying the cost components one at a time (i.e. using the best and worst case scenario based on the lower and upper bound of the base costs, respectively) to determine the main cost drivers. Baseline costs were provided in Table 16 above.

b. Multi-way sensitivity analysis

As multiple costs are uncertain, we also conducted a multi-way sensitivity analysis to account for the best and worst case scenarios.[163] Therefore, we set all the costs to the extreme values using the lower bound (or upper bounds) to obtain the ICER of the best case scenario (or worst case scenario). Lower and upper bound costs were based on the 95% confidence intervals. Where confidence intervals were not available, we used 50% higher and lower than the base case as the upper and lower bound, respectively.

c. Cost-effectiveness acceptability curves

We estimated cost-effectiveness acceptability curves (CEAC) to assess the uncertainty associated with the ICER estimates. We estimated the CEAC from the joint distribution of incremental costs and incremental effectiveness estimated using non-parametric bootstraps

methods. Specifically, we randomly drew a sample of children from the treatment and control groups and estimated the mean incremental effectiveness and costs. We then calculated the ICER from the estimated effectiveness and costs of costs of 1500 replications. To reduce bias with the bootstrap estimates, our bootstrap replications were more than the recommended 1000 replications.[161,162] The CEAC was constructed by calculating the proportion of bootstrap replicas falling within the acceptable willingness-to-pay threshold.[160]

d. Sensitivity analysis- complete case analysis

As we assumed some children that were not in the follow-up survey died, we conducted a complete case analysis using the sample of children that were in both wave 1 and wave 2 of the data. We included 921 children aged 0 to 7 years interviewed in both 2007 and 2009, lived in households that were in treatment and control groups and had complete data (outcome and covariates). We used the complete case sample of the previous study that analyzed the effectiveness of the CT-OVC.[15] This study sample represented 79.3% of the original sample of children aged 0-7 years old that were in the same intervention group in 2007 and 2009. However, we did not assign a reduction in the life expectancy following an illness of malaria and pneumonia considering the 2-year time horizon of the study. Although all children in the study sample are alive in 2007 and 2009, getting malaria or pneumonia has long term impacts on health and consequently life expectancy.[138]

4.3. Results

4.3.1. Effectiveness

Replicating the effectiveness of the CT-OVC, we report the odds ratios associated with a child getting pneumonia or malaria (Table 17). We found that children in households that received the CT-OVC were less likely to get ill. Specifically, children in the treatment group had 0.605 [95% CI: 0.414-0.885] lower odds of getting pneumonia/malaria compared to children in the control. Compared to children aged 5-7 years old, children aged 1-2 years were more likely to get ill. The higher the age of the caregiver, the lower the odds of the child getting pneumonia/malaria. Children living in rural areas and with higher food insecurity had high odds of getting ill, while those in crowded households were less likely to get ill.

Table 17: Effectiveness of the CT-OVC

	Pneumonia/ Malaria	
	Odds ratios	**CI**
CT-OVC	**0.605*** **	**[0.414 - 0.885]**
Post	1.168	[0.840 - 1.624]
Treatment status	1.744	[0.786 - 1.415]
Age Ref: 5 – 7 years		
Under 1 year	1.415	[0.897 - 2.230]
1 – 2 years	1.531***	[1.134 - 2.067]
3 – 4 years	1.102	[0.867 - 1.401]
Male child	0.888	[0.727 - 1.084]
Orphan status	0.918	[0.734 - 1.147]
Child/Grandchild	0.898	[0.614 - 1.315]
Female household head	0.949	[0.760 - 1.185]
Age of household head	0.993**	[0.987 - 0.999]
Household head education	1.011	[0.984 - 1.039]
Rural	1.451***	[1.105 - 1.903]
Mosquito net	1.018	[0.804 - 1.289]
Unprotected/open water source	1.105	[0.890 - 1.372]
Poor cook fuel quality	1.236	[0.204 - 7.501]
Crowding index	0.940**	[0.897 - 0.986]
Asset/wealth index	0.942	[0.865 - 1.026]
Food insecurity	1.307**	[1.042 - 1.641]
Food expenditures	1.000	[1.000 - 1.000]
Food variety	1.038**	[1.008 - 1.069]
Constant	0.744	[0.123 - 6.120]
Observations	1,842	
Number of children	921	

Abbreviations: CT-OVC, cash transfer program for Orphans and Children, CI, confidence intervals

4.3.2. Incremental effectiveness

The CT-OVC program reduced child illnesses amongst children less than seven years. The average DALYs for the treatment group was estimated as 1.80 (95% CI 1.78 – 1.82) and in the control was estimated as 2.01 (95% CI 1.98 – 2.05; Table 18). The incremental effectiveness was 0.212 (95% CI 0.174 - 0.251) DALYs averted.

Table 18: Effectiveness and Incremental Effectiveness

	Child Illness	**95% CI**
DALYs in treatment group	1.80	[1.78 – 1.82]
DALYs in the control group	2.01	[1.98 - 2.05]
Incremental Effectiveness (DALYS)*	**0.212**	**[0.174 - 0.251]**

Abbreviations: CI, confidence intervals; DALYs, Disability adjusted life years
*Based on results of the GEE model

4.3.3. Economic costs

The economic costs stratified by treatment and control group are presented in Table 19. From the healthcare perspective, the mean total cost per child in the treatment group was US$152.80 [95% CI 149.77-155.84]] compared with US$0.94 [95% CI 8.88-0.99] in the control. Similarly, the mean costs were higher in the treatment (US$212.42 [95% CI 208.58-216.25]) compared to the control (US$7.09 [95% CI 6.67-7.51]) from the societal perspective. The cash transfer administration was the highest cost in the treatment group (US$151.99 [95% CI 148.96-155.03]]) while caregiver time was the highest cost in the control group (US$7.17 [95% CI .77-7.56]).

4.3.4. Incremental costs

The CT-OVC had an incremental cost of US$146.83 [95% CI 142.83 – 50.83] from the healthcare perspective and US$193.3 [95% CI 186.2 - 200.5)] from the societal perspective (Table 20). Incremental costs also differed based on age, orphan status, water source and cooking fuel quality

Table 19: Mean cost per participant in treatment versus control, 2018US$

	Treatment		Control		
	Mean	**95% CI**	**Mean**	**95% CI**	**p-value***
CT-OVC					
Cash transfer payment	40.11	[39.31-40.91]	0	-	<0.001
Administration	151.99	[148.96-155.03]	0	-	<0.001
Medications	0.167	[0.159-0.175]	0.189	[0.178-0.199]	0.0007
Nurse Salary	0.058	[0.056-0.061]	0.066	[0.063 - 0.069]	<0.001
Health facility	0.76	[0.722-0.827]	0.862	[0.814-0.91]	<0.001
Patient costs					
Transport (cash transfer)	14.17	[14.17-14.17]	0	-	<0.001
Transport (clinic visit)	0.145	[0.1470.159]	0.166	[0.567-0.175]	<0.001
Care giver time	6.31	[6.00-6.61]	7.17	[6.77-7.56]	<0.001
Total cost (healthcare perspective)	**152.80**	**[149.77-155.84]**	**0.94**	**[0.88-0.99]**	**<0.001**
Total cost (societal perspective)	**212.42**	**[208.58-216.25]**	**7.09**	**[6.67-7.51]**	**<0.001**

* The p-values were from tests of medians based on the Wilcoxon rank sum tests. Abbreviations: CI, confidence interval

Table 20: Incremental costs of the CT-OVC, (US$2018)

	Healthcare perspective		Societal perspective	
	Estimate	95% CI	Estimate	95% CI
CT-OVC	**146.83*** **	**(142.83 – 50.83)**	**193.3*** **	**(186.2 - 200.5)**
Post	1.858*	(-0.177 - 3.893)	2.768*	(-0.0652 - 5.601)
Ref: 5 – 7 years				
Age: under 1 year	-2.925	(-8.660 - 2.810)	1.161	(-6.792 - 9.114)
Age: 1 – under 3 years	-1.713	(-5.796 - 2.370)	1.713	(-3.784 - 7.210)
Age: 3 – under 5 years	-0.132	(-2.500 - 2.236)	0.941	(-2.328 - 4.210)
Male child	0.00660	(-4.597 - 4.611)	-1.140	(-7.161 - 4.882)
Orphan status	1.245	(-1.789 - 4.279)	0.955	(-3.212 - 5.123)
Child/Grandchild	-2.720	(-7.474 - 2.035)	-5.474	(-12.10 - 1.148)
Female household head	-4.581	(-10.12 - 0.959)	-5.271	(-12.38 - 1.837)
Age of household head	0.0263	(-0.0274 - 0.0800)	-0.00563	(-0.0830 - 0.0718)
Household head education	0.0651	(-0.349 - 0.479)	0.164	(-0.416 - 0.744)
Rural	4.119	(-2.559 - 10.80)	6.895	(-1.794 - 15.58)
Mosquito net	1.125	(-1.435 - 3.686)	1.963	(-1.561 - 5.486)
Unprotected/open water source	0.328	(-1.867 - 2.522)	1.701	(-1.364 - 4.765)
Poor cook fuel quality	-23.05**	(-45.79 - -0.313)	-32.12**	(-62.00 - -2.233)
Crowding index	-1.671***	(-2.160 - -1.181)	-2.342***	(-3.015 - -1.668)
Asset/wealth index	-0.101	(-0.709 - 0.507)	-0.0557	(-0.914 - 0.802)
Food insecurity	0.0934	(-2.735 - 2.921)	1.531	(-2.303 - 5.366)
Food expenditures	-0.000326	(-0.00194 - 0.00129)	-0.000119	(-0.00230 - 0.00206)
Food variety	0.0623	(-0.190 - 0.315)	0.200	(-0.153 - 0.552)
Seasonality	1.268**	(0.185 - 2.351)	1.464*	(-0.0363 - 2.965)
Constant	21.17*	(-3.770 - 46.11)	36.60**	(3.422 - 69.77)
Observations	2,224		2,224	2,224
Number of children	1,112		1,112	1,112

4.3.5. Incremental cost-effectiveness ratio (ICER)

We present the calculated ICER in the base case scenario from the healthcare and societal perspectives (Table 21). The ICER of the CT-OVC with respect to reducing child illness from the healthcare perspective was US$691.27 [95% CI 575.68-806.86] per DALY averted and US$939.82 [95% CI 752.14-1127.51] per DALY averted from the societal perspective. Given the GDP per capita of Kenya (2018) of US$1710.51, the CT-OVC is cost-effective in reducing child illness since the ICER is less than 3 times the per-capita GDP (<US$5,131.53). Additionally, the CT-OVC is highly cost-effective as the ICER from both the healthcare and societal perspective is less than the per-capita GDP.

4.3.6. Uncertainty analysis

a. One-way sensitivity analysis

The main cost drivers are presented in the one-way sensitivity analysis (Figure 2). The cash transfer administrative cost and cash transfer payment are the main cost drivers. For instance, taking the best-case scenario of the cash transfer payment (US$35.76) reduces the ICER from US$939.82 to US$593.94 per DALY averted from the societal perspective. Taking the worst-case scenario of the administrative cost of the cash transfer would increase the ICER to US$1285.56 per DALY averted. The CT-OVC is still cost-effective and highly cost-effective in all scenarios of the one-way sensitivity analysis.

b. Multi-way sensitivity analysis

In the best-case scenario, the CT-OVC is highly cost-effective (ICER<1X Kenya's per capita GDP) from both the societal and healthcare perspective (Table 22). In the worst-case scenario, the CT-OVC is still highly cost-effective in reducing child illnesses among orphans and vulnerable children from the healthcare perspective and societal perspective.

c. Sensitivity analysis – complete case analysis

The finding of the sensitivity analysis that the CT-OVC is not cost-effective (Appendix C6) should be interpretated with caution. The high ICER is being driven by limitations of sample restriction, complete case analysis, to only children that were alive in the two waves of data used. This may have underestimated the DALYs as we do not account for years of life lost. As the denominator in the ICER ratio gets smaller or is underestimated, the cost-effectiveness ratio gets larger and is potentially over-estimated.

Table 21: Incremental cost-effectiveness ratios of CT-OVC

	Healthcare perspective		**Societal perspective**	
	Estimate	95% CI*	Estimate	95% CI*
Incremental effectiveness (DALYs averted)	0.21	**[0.174 - 0.251]**	0.21	**[0.174 - 0.251]**
Incremental cost (US$)	146.8	(142.83 – 50.83)	199.63***	(194.52-204.73[
ICER	**691.27**	**[575.68-806.86]**	**939.82**	**[752.14-1127.51]**

Abbreviations: CI, confidence intervals; DALYs, disability adjusted life years; ICER, incremental cost-effectiveness ratio; US$, United States Dollars

*95% CI generated using the bootstrap method

Table 22: Multi-way sensitivity analysis of the cost-effectiveness of the CT-OVC: best and worst cases

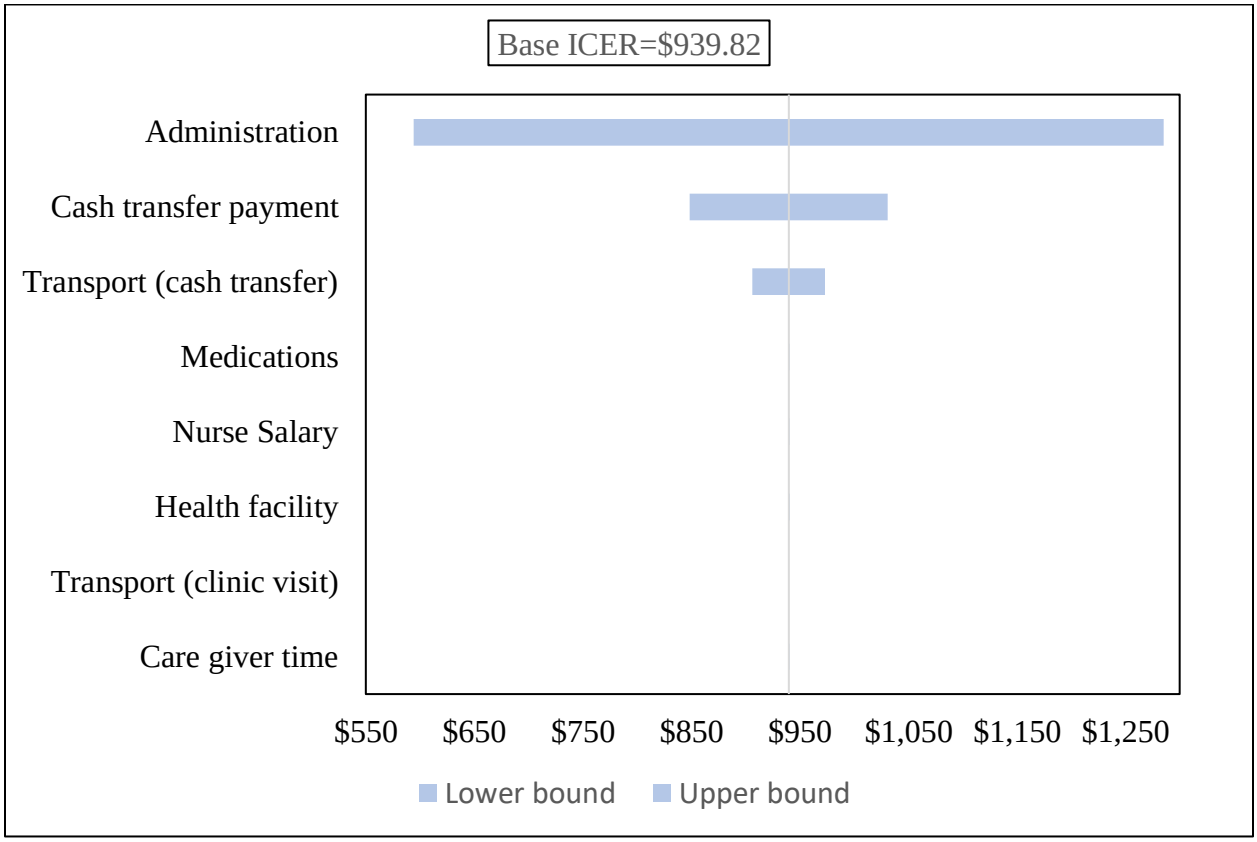
	Healthcare perspective		**Societal perspective**	
	Estimate	95% CI*	Estimate	95% CI*
Best case scenario:				
Incremental effectiveness (DALYs averted)	0.21	**[0.174 - 0.251]**	0.21	**[0.174 - 0.251]**
Incremental cost (US$)	73.42	[71.42-75.41]	99.82	[97.27-102.37]
ICER	**345,64**	**[274.31-416.97]**	**469.96**	**{342.59-597.31]**
Worst case scenario:				
Incremental effectiveness (DALYs averted)	0.21	**[0.174 - 0.251]**	0.21	**[0.174 - 0.251]**
Incremental cost (US$)	220.25	[214.26-226.25]	299.45	[291.80-307.10]
ICER	**1036.92**	**[744.84-1328.99]**	**1409.79**	**[1053.54-1766.03]**

Abbreviations: CI, confidence intervals; DALYs, disability adjusted life years; ICER, incremental cost-effectiveness ratio; US$, United States Dollars

*95% CI generated using the bootstrap method

The best-case scenario was estimated by using the lower bound values for all cost components. The worst-case scenario was estimated using the upper bound values for all costs

Figure 3: One-way sensitivity analysis of changes in unit costs on the ICER, societal perspective



4.3.7. Cost-effectiveness acceptability curves and willingness-to-pay for CT-OVC

We examined the uncertainty associated with the cost-effectiveness of the CT-OVC. Figure 3 presents the joint distribution of the differences in costs and effects of CT-OVC in reducing pneumonia/malaria from 1500 bootstrap samples. All the bootstrapped data is on the northeast quadrant of the cost-effectiveness plane showing that the cash transfer program increases both the costs and effects (DALYs averted). The cost-effectiveness acceptability curve shows the probability that the cash-transfer is cost-effective given varying willingness-to-pay thresholds (Figure 4). The probability that the CT-OVC is cost-effective reaches 1 at a willingness-to-pay threshold of $1287 dollars which is still less than Kenya's GDP per capita, therefore at this

willingness to pay threshold the CT-OVC will always be cost-effective. Given the base case scenario ICER of US$939.82 the probability of being cost-effective is 96.4%%.

Figure 4: Differences in in costs and effects from the societal perspective

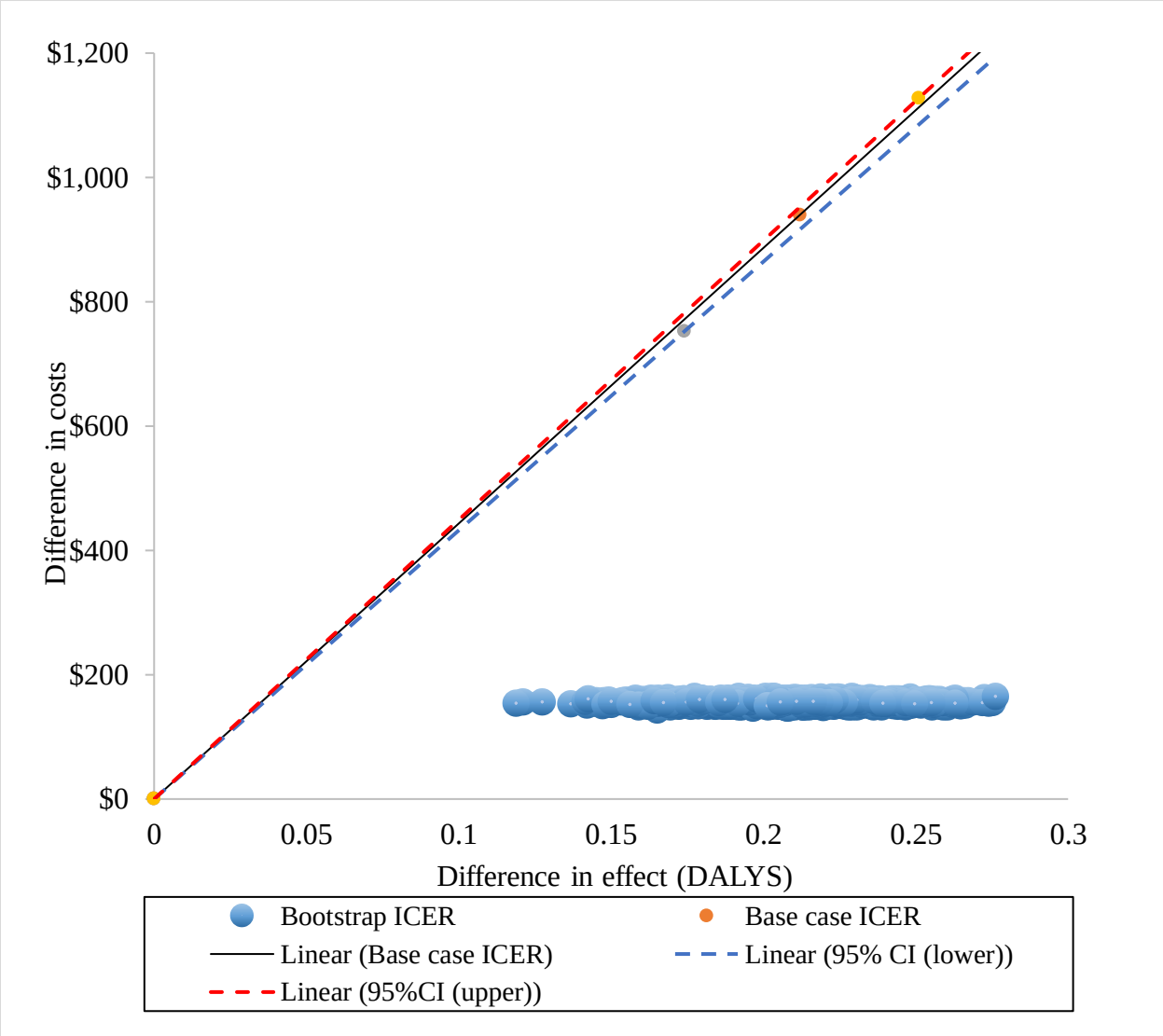
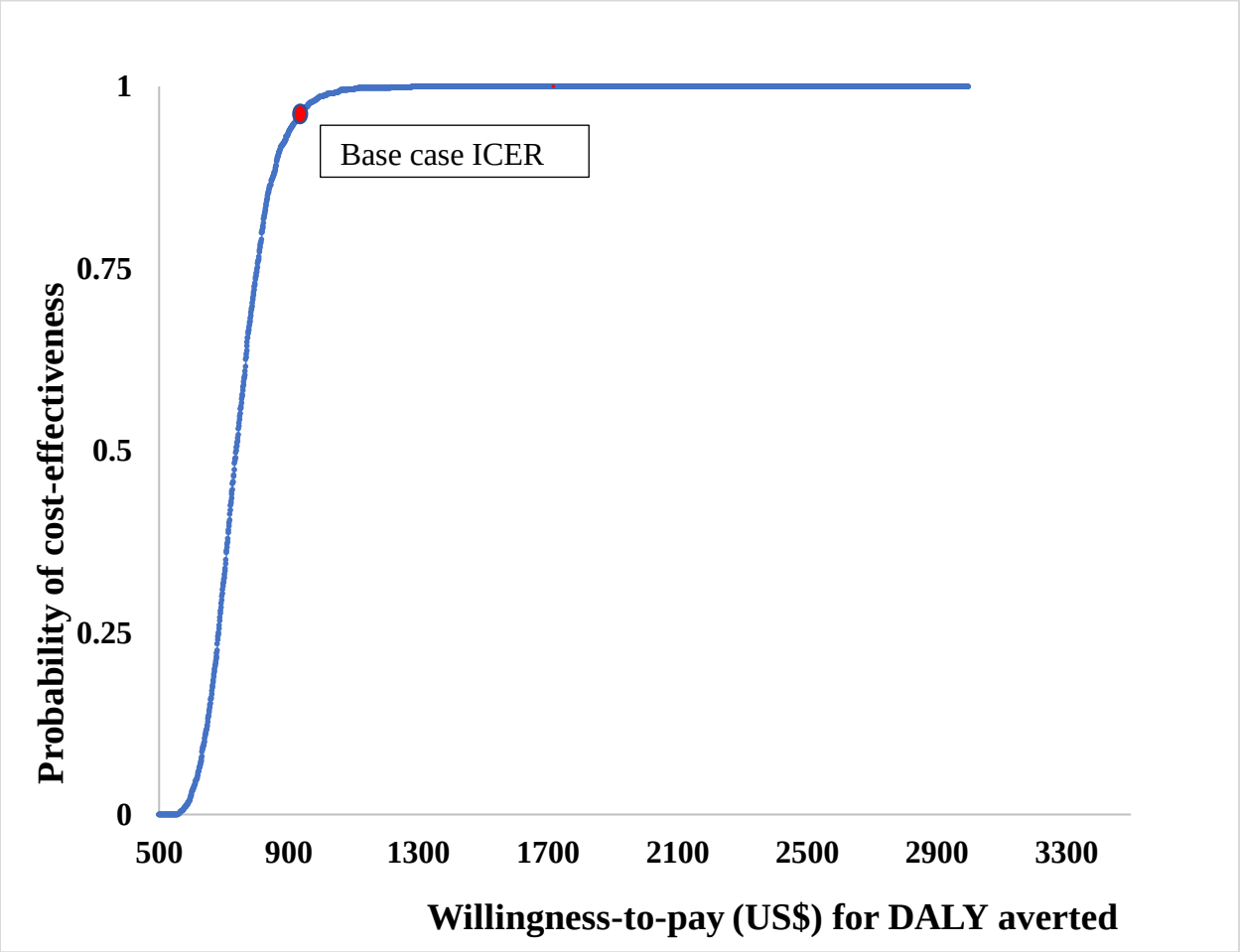


Figure 5: Society's willingness -to-pay for a reduction in malaria and pneumonia in children



4.4. Discussion

We conducted an incremental cost-effectiveness analysis of the CT-OVC in reducing pneumonia and malaria amongst children under seven years of age in Kenya. From the healthcare perspective, the mean total cost per child in the treatment group was US$152.80 [95% CI 149.77-155.84]] compared with US$0.94 [95% CI 8.88-0.99] in the control. Additionally, the CT-OVC had an incremental cost of US$146.83 [95% CI 142.83 – 50.83] from the healthcare perspective and US$193.3 [95% CI 186.2 - 200.5)] from the societal perspective. We found that the CT-OVC is cost-effective and highly cost-effective from both the healthcare and societal perspective. Specifically, the ICER of the CT-OVC with respect to reducing child illness from the healthcare perspective was US$691.27 [95% CI 575.68-806.86] per DALY averted and US$939.82 [95% CI 752.14-1127.51] per DALY averted from the societal perspective.

Our finding that the CT-OVC is a cost-effective strategy is similar to a prior study that found a cash transfer program cost-effectiveness in improving education outcomes[122] but differs from a study conducted in Burkina Faso that did not find a cash program effective in improving child nutrition.[121] While these studies provide evidence on cost-effectiveness of cash transfer programs, our study is the first to our knowledge to examine the cost-effectiveness of a cash transfer program with respect to infectious diseases amongst children. Despite available studies evaluating the cost-effectiveness of various approaches to prevent malaria[125–127] and pneumonia[133–135] in children, none have examined a cash-transfer program as a strategy to reduce these diseases. Further, prior studies have not conducted formal cost-effectiveness analyses,[123,124] and thus we provide evidence by conducting an incremental cost-effectiveness analysis.

This study contributes to the limited literature on cost-effectiveness of cash transfer programs in improving children's health in the sub-Saharan region. As Kenya is a resource limited

country, this cost-effectiveness study contributes to the evidence base to aid decision makers in the country and other developing countries on whether implementing cash transfer programs offers the best value for money amongst the alternate policies aimed to improve child health. There are a number of cash transfer programs being implemented in the sub-Saharan region such as the Child Grant program[164] in South Africa that should be continued as they may reduce illnesses amongst children. Further, policy makers could consider restarting previous cash transfer programs that were discontinued in the region such as Zambia's Child Grant program. Our study provides evidence to support expansion of social protection programs and the major cost drivers such that planners can project the costs required to achieve targeted child health outcomes after expansions.

Additionally, recent prior evidence suggests positive spillover effects of cash transfer programs, as evidenced from a study examining a cash transfer program for pregnant women and mothers of children under one year living in poverty, the Ghana Livelihood Empowerment Against Poverty (LEAP) 2000 program. The LEAP 2000 improved social support for beneficiaries,[106] showing that cash transfer improve beneficiary households beyond the monetary benefits.

4.4.1. Limitations

This study has several limitations. Firstly, the longitudinal cluster-randomized study was not designed for an economic evaluation study and did not collect cost data. We therefore extracted cost estimates from multiple sources which could lead to bias in the cost estimates. However, to reduce the bias of these estimates, we extracted the costs from countries with similar contexts as Kenya. We additionally assessed the uncertainty of the costs using one-way sensitivity analysis and multi-way sensitivity analysis. We found the CT-OVC still cost-effective in the best- and worst-case scenarios of these sensitivity analyses.

Secondly, we did not have data on whether a child died from a case of malaria or pneumonia. We address this limitation by making assumptions about children dying based on reported age-sex mortality rates. However, since we do make assumptions about death, we conducted a sensitivity analysis based on the replication of the sample and effectiveness analysis of the prior study that assessed the impact of the CT-OVC on child illnesses. In this sample, the study restricted the analysis to children who were in both wave 1 and wave 2 datasets. Although we found the CT-OVC not cost-effective in this sensitivity analysis, the estimated DALYs may not be appropriate. As there is a probability of death associated with a case of malaria or pneumonia, the complete cases analysis is potentially underestimating the number of children that were ill. Similar limitations exist with the outcome as this was a self-reported measure based on whether a child was ill in prior months. We anticipate that the ICER estimates from the sensitivity analysis are over-estimated due to the limitations in the measurement of the outcomes. Therefore, to capture the long-term consequence of illnesses in children, including years of life lost is appropriate when estimating DALYs.

An additional limitation of the study is the short time horizon that this study considers. This is particularly a challenge for policy makers that may be interested in assessing how long a program might have value for money to support public allocation planning and decisions. The short time horizon does not enable the analysis to account for practical implementation issues, such as staff turnover, that may make the program more costly and less effective in the long run. Further, the study does not account for unintended consequences, such as community members responsible for selecting the vulnerable children, doing so based on those they have established relationships with. We attempted to address this limitation by using a GEE model to account for theses correlations in our estimation of incremental costs and effectiveness. Although there is the

additional possibility of spillover effects, such that the cash transfer is shared to non-cash transfer households as evidenced with similar cash transfer progamss,[104] the cash transfer amount is small such that we do not anticipate this would significantly impact our ICER estimates. Despite these limitations, our study provides initial evidence upon which future studies can use to project the outcomes and costs of the CT-OVC over a longer time-horizon.

4.4.2. Conclusion

The CT-OVC is cost-effective in reducing infectious diseases amongst children in Kenya. As Kenya is a resource limited country, this cost-effectiveness study contributes to the evidence base to aid decision making in similar sub-Saharan countries, on evaluating alternate strategies that offer the best value for money in reducing illnesses amongst children. Noting that cash transfer programs are more efficient and easier to scale up than other resource intensive programs such as those that involve nutrition supplements or behavior change communication, policy makers should consider expanding current cash transfer programs and restarting discontinued cash transfer programs in the region.

Chapter V: Conclusion

Policy makers play an important role in promoting appropriate healthcare use, especially for low-income individuals who face many barriers to accessing care. Although several policy options are available, this dissertation examined two important policies that can increase the supply of, and demand of health services: provider payments and cash transfer programs. Medicaid plays a crucial role in delivering health services to low-income individuals - providing public health insurance coverage to over 75 million low-income individuals,[4] and about 25 million adult women in the US.[7] Regardless, provider payments are generally lower than other payers, for instance compared to Medicare, and this may have implications beneficiaries access to care.

Given the importance of Medicaid for women's health, changes in the coverage, program's financing and structure have important implications for their access to care.[7] We leverage the state-level variation in physician payments, and use Medicaid claims (2008 -2012) data to examine the association of provider payments and access to SUD treatment amongst women of reproductive age. We found evidence that NH-Black women living in states with higher Medicaid physician fees were more likely to have higher access to SUD treatment. The findings are important for Medicaid policy as increasing physician payments can be used as tool to address the unmet treatment need of minorities, specifically amongst NH-Black women. Addressing the low provider payments in Medicaid markets that disproportionately pay for services for low-income women, can reduce the incidence of SUD among women of reproductive age, and consequently improve other health outcomes.

Further, policy makers may allocate resources to social protection programs, such as cash transfer programs, to address the financial barriers associated with obtaining health services. In Kenya, for instance, the largest social protection program, the Cash Transfer for Orphans and

Vulnerable Children (CT-OVC) disbursed approximately $10 million dollars to households.[66] As with most cash transfer programs in developing countries, there is limited evidence finding the CT-OVC effective in increasing health service utilization.[15] However, we examined the impact of the CT-OVC on child healthcare use and account for the role of economic preferences in moderating the cash transfer program impacts – addressing a major limitation with prior studies.

Understanding whether economic preferences are a modifier in the relationship between cash transfers and healthcare allows a more comprehensive evaluation of cash transfer program effects. We found evidence that a caregiver's time preference moderates the impact of the CT-OVC on child healthcare utilization. Therefore, receiving the CT-OVC enables caregivers to enact on their preferences once budget constraints are relieved. This finding has important policy implications as the evidence from our study can be used to advocate for increased resource allocation to social protection programs to improve children's health.

Finally, we found that the CT-OVC is cost-effective strategy in reducing illnesses amongst children from both the healthcare and societal perspective. As Kenya is a resource limited country, our findings contribute to the evidence base to aid decision makers in the country, and other developing countries, on whether implementing cash transfer programs offers the best value for money amongst the alternate policies aimed to improve child health. Policy makers should consider continuation of discontinued cash transfer programs or increasing the scale of existing programs targeted at vulnerable populations. Policy makers can project the costs required to achieve targeted child health outcomes after expansions based on our findings. However, additional health programming aligned to social protection programs, such cash-plus programs should be considered to reach those with high discount rates should be considered in policy formulation.

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APPENDIX A

Appendix A1: Economic and conceptual framework for paper 1

A1.1. Economic framework

This study is based on Sloan et al (1978)[165] economic framework to explain how an increases in Medicaid physician payments increase the supply of health services for Medicaid patients. For simplicity, this model assumes there are only two markets, Medicaid and the private market, for which a provider can supply units of health services to. In the Medicaid market, the provider accepts payment as payment in full, and is not allowed to obtain additional funds from the patient.[165] Consequently, in the market for Medicaid patients, providers face a perfectly elastic demand curve[40] since the fee schedule in that market is fixed and they would demand the services of another provider in the market if they encounter one who is unwilling to supply the service at the set fee-schedule. Therefore, the Medicaid market represents a price-taking market such that the revenue in the Medicaid market is given by:

$$sx \qquad \text{(i)}$$

Where s is the Medicaid fee schedule and x is the number of units of the health services sold to the Medicaid patient.[165] Administrative costs, such as bill collection costs, are a key component in the providers willingness to supply health services to the Medicaid market and therefore, model (i) is adjusted to:

$$(s - g)x \qquad \text{(ii)}$$

Where g is the administrative cost in the Medicaid market.[165]

In the private market, a provider faces a downward-sloping demand curve[165] because even as a provider charges a higher price for its service, there will still be a market at the new price.[3] In the absence of health insurance, the price-setting demand function is given by:

$$p(y, \bar{g}; M) \qquad \text{(iii)}$$

Where p is the unit price net of bad debts, y is the quantity sold in the private or price-setting market, $\bar{g}$ is the administrative cost associated with the private market and M reflects exogenous variable affecting the provider's demand curve.[165] For instance, M could represent a patient's income, since without insurance coverage, it is the patient's responsibility to pay the provider for the service. A bad debt would arise from the inability of a patient to pay their medical bill.

The price-setting demand function with the presence of Medicaid and private insurance is given by:

$$f(\bar{s}, \bar{g}; M) + p(y, \bar{g}; M) \qquad \text{(iv)}$$

Where *f* is the expected (mean) fee schedule in the private setting market, $\bar{s}$ in the Private market fee schedule, $\bar{g}$ is the administrative cost associated with the private market and M is any exogenous variable, such as patient income, affecting the fee-schedule. In the market represented by (iv), a patient submits a claim to a third party, yet the third-party coverage of the providers services is incomplete as the patient has to pay part of the bill. Therefore, the patient's income would still affect the expected fee schedule in the private market with insurance.

In such a market, the provider maximizes the following function:[165]

$$\pi = (s - g)x + [f(\bar{s}, \bar{g}; M) + p(y, \bar{g}; M) - \bar{g}]y - C(x + y; N) \quad \text{(v)}$$

Where, *C(x+y;N)* is the providers cost function for the cost C associated with seeing a Medicaid patient *x* and private patient *y*. In this simple model, it is assumed that the cost of providing service to a Medicaid patient *Cx* is the same cost as providing it to the private patient *Cy*,[165] so that the cost of seeing a patient in either market does not influence a providers maximization objective. Since providing services to patients is the same regardless of the market,[40] physicians will allocate their time between Medicaid patients *x* and private patients *y* such that marginal revenue in the two markets is equal.[166] Since providers have control over the extent of their involvement with patients,[166] they maximize π by deciding on the levels of x and y while taking into consideration s, $\bar{s}$, g and M.

When Medicaid fees increase relative to the private market, a provider is encouraged to reallocate their work effort so that they supply more services to Medicaid patients. However, the increased Medicaid fees would have to be high enough to induce physicians who mainly saw private patients to now provide their services to the Medicaid market.[166] Thus, an increase in the Medicaid fee rate will entice providers on the margin to provide more services to the patients in the Medicaid market.[40]

Consequently, the present study hypothesizes that higher Medicaid physician fee rates will increase the supply of health supply services to Medicaid patients.

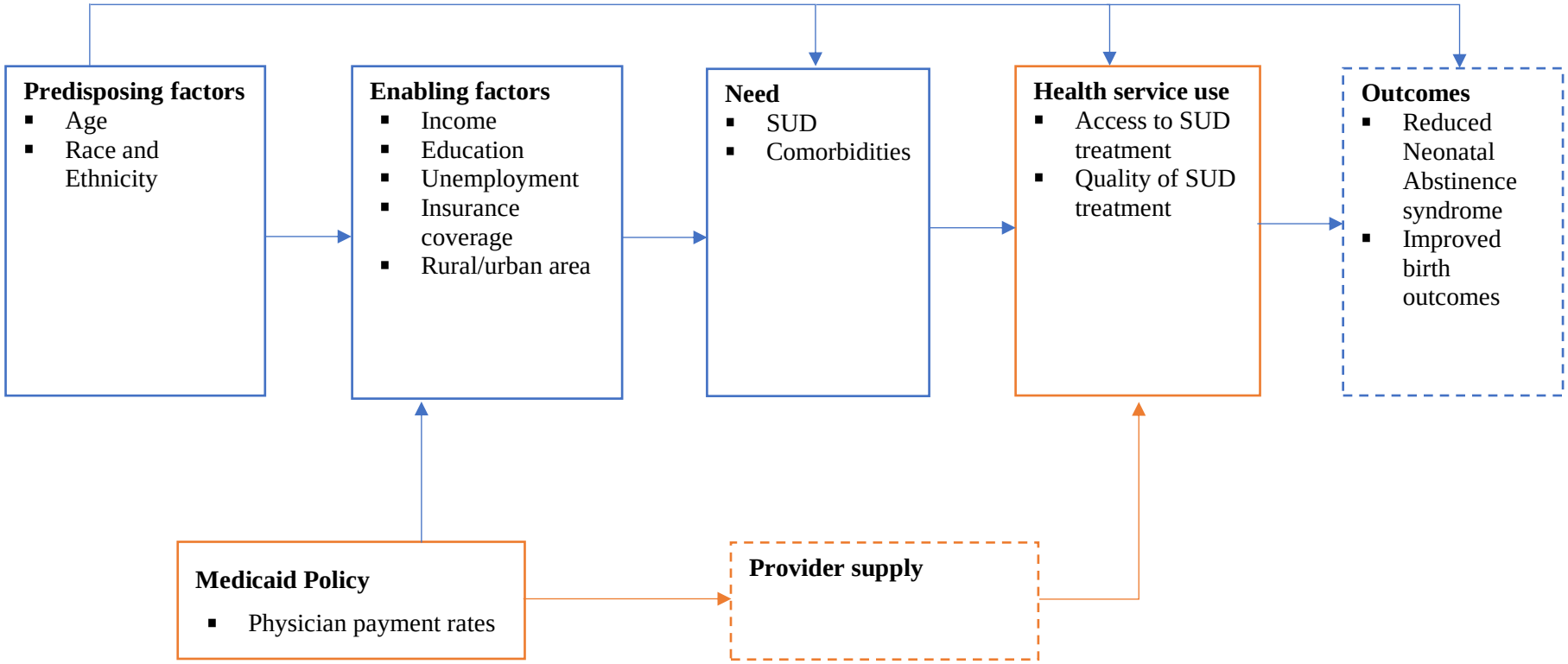
A1.2. Conceptual framework

The conceptual framework for this study is based on Andersen's behavioral model.[57] This model is widely used for explaining healthcare service utlization.[167] The Andersen model shows how the health care system, external environment, predisposing characteristics and enabling resources interact and affect health service utilization.[57,167,168]

Within the healthcare system, Medicaid policy determines the providers reimbursement rates that affect provider availability and improve access and quality of SUD treatment. As described in the economic framework, an increase in Medicaid reimbursement rates will increase the amount of healthcare services supplied to Medicaid patients.[34,40]

With more providers available, Medicaid patient's access to health services will increase with decreases in travel and wait times as potential mechanisms.[29] A crucial implication of this is that a patient is more likely to commence SUD treatment but also to continue with treatment, which is an indicator of treatment quality, once they access care. Moreover, increased access to SUD treatment may also increase access to guideline-concordant preventive and chronic disease management services,[169] as providers are more likely to supply these services when payment rates increase.[41,170]

Figure 6: Conceptual framework for Chapter II



While provider supply may increase the access and quality of SUD treatment, we observe from the Andersen framework that predisposing factors, enabling characteristics and need also affect health care utilization. It should be noted that while these factors may impact health outcomes on their own, the model attempts to provide a causal pathway upon which these components result in the observed health outcomes.[57]

Predisposing factors such as age and race and ethnicity affect SUD treatment utilization. Individuals who are older and White are more likely to have access to SUD treatment[171] and be retained in treatment.[172,173] Enabling characteristics such as income,[174] living in an urban area,[175,176] being employed[174] and having insurance coverage[176] are also associated with higher substance use treatment utilization. Further, the level of need for substance use treatment services will affect treatment-seeking behaviors. For instance, individuals with high comorbidities[11,177,178] and PLWH[178–180] may use more treatment services due to their poor health that increases demand for care.

Although the present study focuses on the intermediate outcome (access and quality of SUD treatment) it is worth noting that with more women of reproductive age receiving higher quality SUD treatment, improvement in health outcomes such as higher infant birthweight babies, reduced sexual transmitted infections and reduced NAS is expected.[21]

Appendix A2: ICD-9 codes for identification of individuals with SUD

Code	Description
Alcohol	
291.0	Alcohol withdrawal delirium
291.1	Alcohol-induced persisting amnestic disorder
291.2	Alcohol-induced persisting dementia
291.3	Alcohol-induced psychotic disorder with hallucinations
291.4	Idiosyncratic alcohol intoxication
291.5	Alcohol-induced psychotic disorder with delusions
291.81	Alcohol withdrawal
291.82	Alcohol induced sleep disorders
291.89	Other alcohol-induced mental disorders
291.9	Unspecified alcohol-induced mental disorders
303.00	Acute alcoholic intoxication in alcoholism, unspecified
303.01	Acute alcoholic intoxication in alcoholism, continuous
303.02	Acute alcoholic intoxication in alcoholism, episodic
303.03	Acute alcoholic intoxication in alcoholism, in remission
303.9	Other and unspecified alcohol dependence, unspecified
303.91	Other and unspecified alcohol dependence, continuous
303.92	Other and unspecified alcohol dependence, episodic
303.93	Other and unspecified alcohol dependence, in remission
305.00	Alcohol abuse
305.01	Alcohol abuse
305.02	Alcohol abuse
305.03	Alcohol abuse
357.5	Alcohol polyneuropathy
425.5	Alcoholic cardiomyopathy
535.30	Alcoholic gastritis
535.31	Alcoholic gastritis
571.0	Alcoholic fatty liver
571.1	Acute alcoholic hepatitis
571.2	Alcoholic cirrhosis of liver
571.3	Alcoholic liver damage, unspecified
E860.0	Alcoholic beverage poisoning
Amphetamines	
304.4	Amphetamine and other psychostimulant dependence, unspecified
304.41	Amphetamine and other psychostimulant dependence, continuous
304.42	Amphetamine and other psychostimulant dependence, episodic
304.43	Amphetamine and other psychostimulant dependence, in remission
305.7	Amphetamine or related acting sympathomimetic abuse, unspecified

305.71	Amphetamine or related acting sympathomimetic abuse, continuous
305.72	Amphetamine or related acting sympathomimetic abuse, episodic
305.73	Amphetamine or related acting sympathomimetic abuse, in remission
Cannabis	
304.30	Cannabis dependence, unspecified
304.31	Cannabis dependence, continuous
304.32	Cannabis dependence, episodic
304.33	Cannabis dependence, in remission
305.20	Cannabis abuse, unspecified
305.21	Cannabis abuse, continuous
305.22	Cannabis abuse, episodic
305.23	Cannabis abuse, in remission
Cocaine	
304.20	Cocaine dependence, unspecified
304.21	Cocaine dependence, continuous
304.22	Cocaine dependence, episodic
304.23	Cocaine dependence, in remission
305.60	Cocaine abuse, unspecified
305.61	Cocaine abuse, continuous
305.62	Cocaine abuse, episodic
305.63	Cocaine abuse, in remission
968.5	Poisoning by cocaine
E938.5	Cocaine, adverse effects
Drug-induced mental disorder	
292.0	Drug withdrawal
292.11	Drug-induced psychotic disorder with delusions
292.12	Drug-induced psychotic disorder with hallucinations
292.2	Pathological drug intoxication
292.81	Drug-induced delirium
292.82	Drug-induced persisting dementia
292.83	Drug-induced persisting amnestic disorder
292.84	Drug-induced mood disorder
292.85	Drug induced sleep disorders
292.89	Other specified drug-induced mental disorders
292.9	Unspecified drug-induced mental disorder
Hallucinogens	
304.50	Hallucinogen dependence, unspecified
304.51	Hallucinogen dependence, continuous
304.52	Hallucinogen dependence, episodic

304.53	Hallucinogen dependence, in remission
305.30	Hallucinogen abuse, unspecified
305.31	Hallucinogen abuse, continuous
305.32	Hallucinogen abuse, episodic
305.33	Hallucinogen abuse, in remission
969.6	Poisoning by hallucinogen
E854.1	Accidental poisoning by hallucinogen
E939.6	Hallucinogens, adverse effects

Other

304.60	Other specified drug dependence, unspecified
304.61	Other specified drug dependence, continuous
304.62	Other specified drug dependence, episodic
304.63	Other specified drug dependence, in remission
304.80	Combinations of drug dependence excluding opioid type drug, unspecified
304.81	Combinations of drug dependence excluding opioid type drug, continuous
304.82	Combinations of drug dependence excluding opioid type drug, episodic
304.83	Combinations of drug dependence excluding opioid type drug, in remission
304.90	Unspecified drug dependence, unspecified
304.91	Unspecified drug dependence, continuous
304.92	Unspecified drug dependence, episodic
304.93	Unspecified drug dependence, in remission
305.90	Other, mixed, or unspecified drug abuse, unspecified
305.91	Other, mixed, or unspecified drug abuse, continuous
305.92	Other, mixed, or unspecified drug abuse, unspecified
305.93	Other, mixed, or unspecified drug abuse, continuous

Sedatives, hypnotics, anxiolytics, tranquilizers, barbituates

305.40	Sedative, hypnotic, or anxiolytic abuse, unspecified
305.41	Sedative, hypnotic, or anxiolytic abuse, continuous
305.42	Sedative, hypnotic, or anxiolytic abuse, episodic
305.43	Sedative, hypnotic, or anxiolytic abuse, in remission
304.10	Sedative, hypnotic, or anxiolytic dependence, unspecified
304.11	Sedative, hypnotic, or anxiolytic dependence, continuous
304.12	Sedative, hypnotic, or anxiolytic dependence, episodic
304.13	Sedative, hypnotic, or anxiolytic dependence, in remission

Opioids

304.00	Opioid type dependence, unspecified
304.01	Opioid type dependence, continuous
304.02	Opioid type dependence, episodic
304.03	Opioid type dependence, in remission
305.50	Opioid abuse, unspecified

305.51	Opioid abuse, continuous
305.52	Opioid abuse, episodic
305.53	Opioid abuse, in remission
E850.0	Accidental poisoning by other opiates and related narcotics
E935.0	Heroin, adverse effects
304.70	Combination of opioids with any other
304.71	Combination of opioids with any other
304.72	Combination of opioids with any other
304.73	Combination of opioids with any other
965.00	Poisoning by opium
965.01	Poisoning by heroin
965.02	Poisoning by methadone
965.09	Poisoning by other opiate and related narcotics

Source:[181]

Appendix A3: Access to SUD - CPT codes for classification of outcomes

CPT Code	Description of CPT Codes	Source
90801	Interview evaluation	182
99205	Induction	183
99215	Induction	183
90805	Stabilization	183
90862	Pharmacologic management	183
99201	Evaluation and management	183、184
99202	Evaluation and management	183、184
99203	Evaluation and management	183、184
99204	Evaluation and management	183、184
99205	Evaluation and management	183、184
99211	Evaluation and management	183、184
99212	Evaluation and management	183、184
99213	Evaluation and management	183、184
99214	Evaluation and management	183、184
99215	Evaluation and management	183、184
99354	Prolonged services	183、184
99355	Prolonged services	183、184
99408	Alcohol and/or substance abuse structured screening and brief intervention services, 15–30 minutes.	185
99409	Alcohol and/or substance (other than tobacco) abuse structured screening (eg, AUDIT, DAST), and brief intervention (SBI) services, greater than 30 minutes	185
9446	Alcoholism counselling	185
9453	Referral alcohol rehab	185
9461	Alcohol rehabilitation	185
9462	Alcohol detoxification	185
9463	Alcohol rehab/detox	185
9467	Comb alcohol/drug rehab	185
9468	Comb alcohol/drug detox	185
99215	Evaluation and management	185
99354	Prolonged services	185
99355	Prolonged services	185
9425	psychiat drug therap nec	185
9445	drug addict counselling	185
9454	referral for drug rehab	185
9464	drug rehabilitation	185
9465	drug detoxification	185
9466	drug rehab/detox	185
9467	comb alcohol/drug rehab	185
9468	comb alcohol/drug detox	185
9469	comb alco/drug reha/deto	185
H0049	Alcohol and/or drug screening	185
H0050	Alcohol and/or drug service, brief intervention, per 15 minutes	185
H0049	Alcohol and/or drug screening	185

Appendix A4: Sensitivity analyses for paper 1

Appendix 4.1: Sensitivity analysis – Sample using 2008 and 2012 data only

	Full sample(n=4616)		**NH-Whites (n=2276)**		**NH-Black (n=1789)**	
	β	**Standard error**	**β**	**Standard error**	**β**	**Standard error**
Medicaid-to-Medicare fee ratio	0.02479	0.03459	0.020	0.049	0.147***	0.058
Age (ref: NH-White):						
NH-Black	-0.04***	0.01314				
Hispanic	-0.01958	0.02753				
Other	-0.02537	0.02671				
Age (ref: <+45years):						
<25 years	-0.12***	0.01978	-0.112***	0.02964	-0.129***	0.02939
25-34	-0.06***	0.01697	-0.045**	0.02620	-0.077***	0.02362
35-44 years	-0.031***	0.01534	-0.048***	0.02538	-0.019	0.01979
Share of the population employed, county	-3.19675	1.47920	-3.79***	1.97	1.85885	2.78475
Share of the population with more than high school, county	0.00330	0.00190	0.00420	0.00299	0.00176	0.00400
Share of the population living in an urban area, county	-0.18799	0.18318	-0.54***	0.249	0.36569	0.32220
Comorbidity	0.00803	0.01997	0.03800	0.02611	0.01845	0.03876
Average household income (ln ($)), county	-0.00532	0.01197	-0.00777	0.01791	-0.02954	0.01667
Managed care	0.01436	0.02748	0.02693	0.04073	-0.01768	0.03595
SUD prevalence (%)	-0.18***	0.02729	-0.21***	0.04	-0.099**	0.03793
Intercept	-56.29**	21.55754	-13.902	23.83532	-158.8***	39.15416

**controlling for year and state fixed effect;* *** p<0.01; ** p<0.05; * p<0.10; reporting linear probability model estimates

Appendix A4.2: Sensitivity analysis- Alternative model specification including an interaction term

	Full sample (n=7128)	
	β	Standard error
Medicaid-to-Medicare fee ratio * Minority (black=1)	0.22***	0.08622
Medicaid-to-Medicare fee ratio	0.01855	0.02604
Minority	-0.23***	0.06951
Age (ref: 45+ years):		
<25 years	-0.166***	0.01798
25-34	-0.065***	0.01524
35-44 years	-0.029**	0.01328
Share of the population employed, county	0.0018**	0.01637
Share of the population with more than high school, county	-0.02045	0.01069
Share of the population living in an urban area, county	0.02451	0.02572
Average household income (ln ($)), county	-0.20297	0.02328
Comorbidity	-2.56*	1.24268
Managed care	0.00204	0.00182
SUD prevalence (%)	-0.24***	0.16411
Intercept	-53.59***	16.04128

**controlling for year and state fixed effects;* *** p<0.01; ** p<0.05; *p<0.1; reporting linear probability estimates

Appendix A4.3: Sensitivity analysis- Sample including those enrolled in managed care only

	Full sample (n=6661)		NH-Whites (n=3338)		NH-Black (n=2282)	
	β	Standard error	β	Standard error	β	Standard error
Medicaid-to-Medicare fee ratio	0.02321	0.02530	-0.032	0.04262	0.08***	0.030
Age (ref: NH-White):						
NH-Black	-0.056***	0.01205				
Hispanic	0.04500**	0.02070				
Other	-0.02912	0.02172				
Age (ref: <25 years):						
25-34	0.109***	0.01764	0.11***	0.02386	0.08***	0.02938
35-44 years	0.150***	0.01633	0.12***	0.02288	0.118**	0.02660
45+ years	0.185***	0.01755	0.18***	0.02531	0.128***	0.02822
Share of the population employed, county	-4.05***	1.22691	-3.83498	1.63002	-1.00182	2.45417
Share of the population with more than high school, county	0.00516	0.00153	0.00344	0.00237	0.00162	0.00347
Share of the population living in an urban area, county	-0.16881	0.16222	-0.38*	0.22124	0.05760	0.29272
Comorbidity	-0.00022	0.01055	-0.00868	0.01551	-0.03**	0.01547
Average household income (ln ($)), county	-0.02359	0.01596	0.00676	0.02110	-0.04582	0.03034
SUD prevalence (%)	-0.1493***	0.03921	-0.19***	0.05594	-0.09*	0.05371
Intercept	-55.85154	15.72465	-12.21	24.43322	-120.51	22.10625

**controlling for year and state fixed effect;* *** p<0.01; ** p<0.05; * p<0.10; reporting linear probability estimates

APPENDIX B

Appendix B1: Economic and conceptual framework for paper 2

B1.1. Cash transfers and healthcare utilization

Traditional economic theory provides a framework on how cash transfers may influence healthcare use. A simplified consumer demand model states that the demand for services (D_h) is a function of the price of the service (P_h), the price of an alternative service (P_a), income (I) and preferences, including economic preferences (E):[3]

$$D_h = f(P_h,\ P_a, I, E) \qquad \text{(i.a)}$$

Subject to a budget constraint I:

$$P_h X_h + P_a X_a = I \qquad \text{(i.b)}$$

Such that X_h is the quantity of service and X_a is the quantity of an alternative service.

When there is an exogenous increase in income, such as through a cash transfer program, the budget constraint increases allowing for an individual to demand more health services.[3]

B1.2. Time preference and healthcare utilization

An individual's preference for current consumption of a good or service is determined by their valuation of future consumption. The discounted utility (DU) model assumes that the motivation for intertemporal choice involves a single parameter – a discount rate- such that:[78]

$$U^t(c_t, \dots, c_T) = \sum_{k=0}^{T-t}\left(\frac{1}{1+p}\right)u(c_{t+k}) \qquad \text{(ii)}$$

So that the utility obtained from the preference over consumption profiles ($c_t,\dots c_T$) is the total utility they derive from consumption in period $t+k$ factoring in $D(k)$ -the relative weight they place on their well-being in period t to their well-being in period $t+k$.[78] This intertemporal utility function represents individual preference that assumes a person evaluates new alternatives by integrating them within existing plans.[78] In the context of the present study on healthcare use, individuals face a choice of spending the money and time on current healthcare utilization that has some future benefit or using their money and time now for other goods and services that have smaller more immediate benefits. Their decision to spend money and time for healthcare in the present period t will depend on whether they value the future benefit in period $t+k$.

To understand how caregivers' time preference may influence children's healthcare use, consider the following. Rosenzweig and Schultz's (1983) model for child health production is given by the utility function:

$$U = U\big(X_i, Y_j, H\big), i = 1 \dots, n; j = n+1, \dots, m \qquad \text{(iv)}$$

Such that a caregiver's utility is derived from their child's health H, the consumption of goods and services that do not affect a child's health X and goods and services that affect a child's health Y. Given that consumption profiles exist across time periods as shown in (ii) and the utility from a consumption profile is based on an individual's discount factor (iii), a caregiver's utility function discounts the consumption bundle X, Y and H given as:

$$c_t = \sum_{t=0}^{T} C_H + C_X + C_Y \quad \text{(v)}$$

where C_H, C_X and C_Y represent consumption of *H*, *X* and *Y* in a time period, respectively. Consequently, the DU model would apply to (iv) such that a caregiver discounts the utility associated with their child health. That is, caregivers' time preferences affect decisions about their children's health because child health is in their utility function. Therefore, as described in (i.a) a caregiver's discount rate represented in *E* will affect the cash transfer program impact on the demand children's health care utilization D_h.

B1.3. Risk preference and healthcare utilization

Decisions that involve uncertainty or risk, ones where there are more than one possible outcome along with the probability associated with each outcome are influenced by individual's risk aversion.[186] Therefore, choices between options with uncertain outcomes, like using preventive health care services, can be modelled using expected utility.[186] The expected utility model postulates that a person has a utility function that assigns a "utility" to each possible outcome such that a person chooses an outcome with the highest expected utility.[186] Therefore, the expected utility function can be defined as:[187]

$$EU(A) = \Sigma_{o \in O} P(A) * U(A) \quad \text{(vi)}$$

Where the expected utility EU of a caregiver A is given by the probability *P* of an outcome *o* and $U(.)$ is the utility associated with an outcome. Given the utility function in (iv), a caregiver will maximize the expected utility against a set of possible benefits and losses of children's preventive healthcare use. Alternatively, (vi) can be represented as:[188]

$$P * U(Y - L) + (1 - P) * U(Y) \quad \text{(vii)}$$

Where in the context of the current study Y is defined as the gains from child healthcare utilization of preventive services and L is the loss or consequence associated with not using preventive services. Consequently, the impact of increased income from the cash transfer of child health care use may vary depending on the weight a caregiver places on the loss of child health from not using preventive healthcare, or their level of risk aversion.

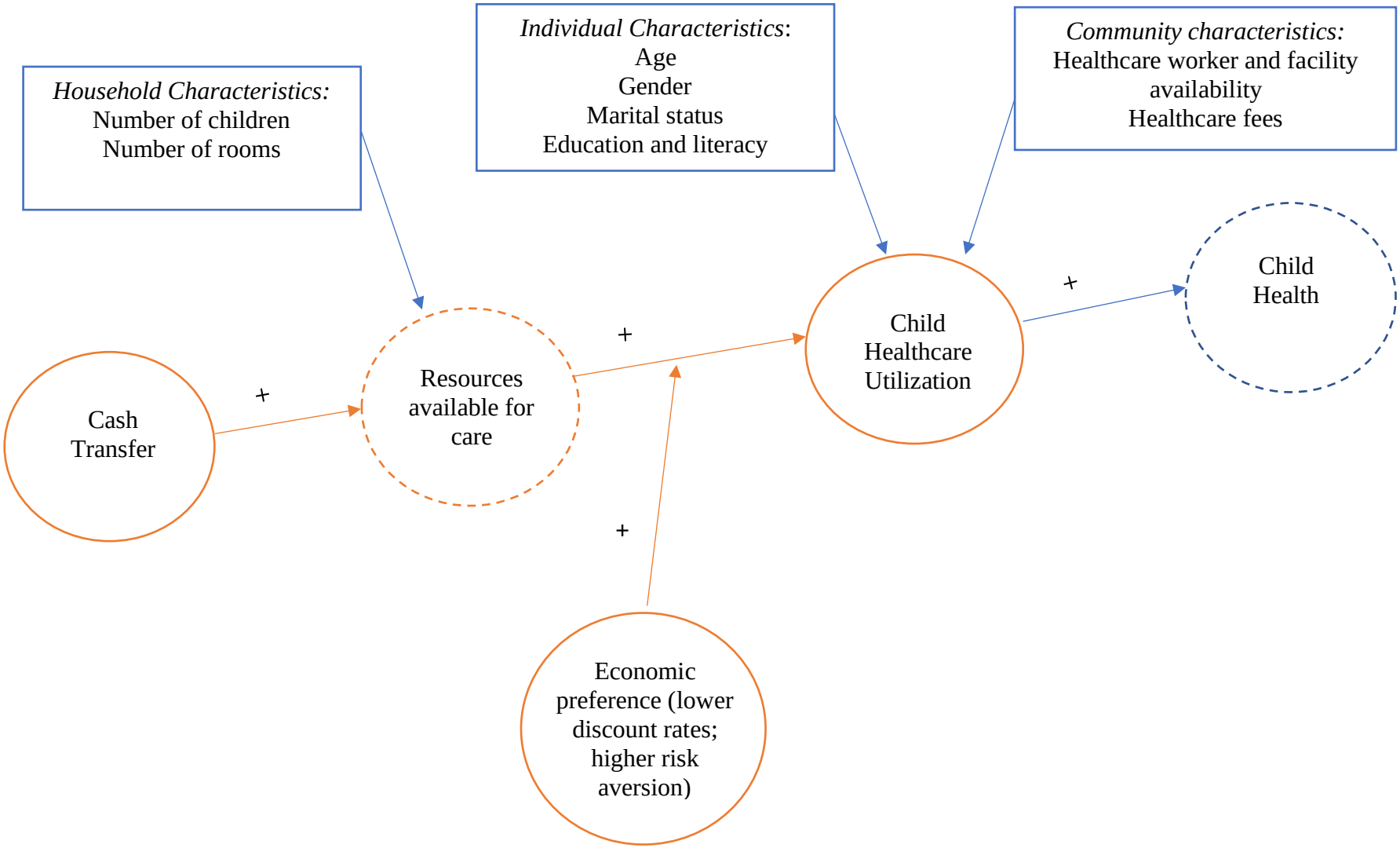
B1.4. Conceptual framework

The economic framework described above provides the basis of the conceptual framework shown in Figure 3. Traditional economic theory suggests that an increase in income will expand the budget such that there are more resources available at an individual's disposal.[3] The resources available through a cash transfer to low-income households may increase access to care.[189] With the increased accessibility of healthcare services, households can demand more services. However, whether they demand health services also depends on their economic preferences (discount rate and risk aversion).

Traditional economic theory states that economic preferences are predetermined when a consumer enters a market.[3] Therefore, while income may increase and these preferences remain unchanged, it is plausible that demand for that service may remain unchanged – depending on their discount rate and risk aversion. This raises an important implication for the study of cash transfers

on healthcare utilization as economic preferences shape demand, and consequently healthcare use. While there is some evidence that economic preferences can change with additional income as it allows households to contemplate delaying consumption,[190] prior evaluation of the CT-OVC found no impact of the cash transfer on time and risk preferences.[91] Therefore, economic preferences are considered in this study to be exogenous but they are expected to moderate the impact of the cash transfer program on children's healthcare utilization.

Figure 7: Conceptual framework for Chapter III



An assumption of the DU model is that a consumer has sufficient information about the future benefits of consumption to be able to value consumption profiles across time periods.[78] Education and literacy of caregivers therefore becomes important in decisions about their children's health care utilization.[96] It is worth noting that, while the increase in income will determine healthcare use, the initial level of income or wealth[95] will also determine whether or not there will be an increase in demand. It is possible that extremely poor households with low or no income will receive cash transfers, but this income will not be sufficient to offset current competing demands such that there will be an increase in consumption of other goods depending on their preference (that is X in (iv) as opposed to Y in the economic framework). However, in poor households, household spending serves as a proxy for resource constraints and competing demands for the household.[96] Further, in poor households, the number of rooms proxies the level of wealth.[99] Consequently, the conceptual model incorporates household spending, the number of rooms and the number of children to account for these tradeoffs.

Additionally, while a caregiver may desire increased healthcare use for their child, the supply of healthcare must be available to meet the demand for these services.[96] For instance, there needs to be facilities available for caregivers to actually seek care, enough staff to manage the demand at these healthcare facilities and medications for treatment.[12] In addition, the costs of seeking care, such as cost of vaccinations may impact demand for health services.

Finally, demographic factors also play a role in the demand for healthcare. Taking an example of age, an older individual may have more experience raising a child and may not seek treatment for a child experiencing a symptom from prior experience.[96] Altogether, Figure 3 represents how a cash transfer, economic preferences, and individual, household and community characteristics play a role in child healthcare utilization.

Appendix B2: Child healthcare utilization survey questions

Has a health card: Whether or not a child has a health card is created as a binary measure based on the following survey question: "Does [NAME]have a health card (vaccination card, growth monitoring card)?" As a health card is usually provided with a birth or visit to a healthcare facility,[90] this serves as an indicator of child healthcare utilization.

Receipt of tuberculosis vaccination: A binary measure for whether a child had a BCG vaccination against tuberculosis was created using a combination of recorded information by the survey interviewer from the health card. Where the health card was not available, I use the self-reported measure based on the following survey question: "Has [NAME] received BCG vaccination against tuberculosis, that is, an injection in the left arm that usually causes a scar?"

Receipt of DPT/Hep/Flu vaccination: A binary measure for whether there is any record for a vaccination against DPT, Hepatitis C, or Flu on the health card. While these are independent vaccines, the health card reports this as a single record if any of the vaccines were received. Therefore, where a health card was not available, I combine the self-reported measure based on the following survey question: "Has [NAME] received DPT vaccination, that is, an injection in the thigh, sometimes at the same time as polio drops?"

Number of DPT vaccinations: Similar to the receipt of DPT/Hep/Flu above, a continuous measure for the number of times these vaccinations was recorded on the health card (out of 3) was created. If the respondent did not have the health card, I use the response to the question: "How many times was the DPT vaccine received in total?"

Receipt of Polio vaccination: A binary measure for whether there is a record on the health card for any vaccination against Polio was created. Where a health card was not available, I use the self-reported measure based on the following survey question: "Has [NAME] received Polio vaccination, that is, drops in the mouth?"

Number of Polio vaccinations: A continuous measure for the number of times a Polio vaccination was recorded on the health card (out of 4). If the respondent did not have the health card, I use the response to the question: "How many times was the Polio vaccine received in total?"

Measles: A binary measure for whether a child received a vaccination against measles was created based on the following question: "Has [NAME] received an injection in the upper right arm to prevent measles?"

Diarrhea treatment: Respondents for children under the age of five were asked if the child had diarrhea in the last six months: "Has [NAME] had diarrhea in the last month?" For those responded yes, I create a binary measure for whether or not treatment was sought for diarrhea based on the follow-up question: "Did you seek advice or treatment for the diarrhea?" This question was asked to all respondent regardless of whether they had a health card or not.

Cough/fever treatment: Amongst children who had a cough or fever, or an illness with a cough, I create a binary measure based on the following question: "Did you seek advice or treatment for

the fever/cough from a health facility, pharmacy, shop, or other person"? This question was also asked to all respondent regardless of whether they had a health card or not.

Vitamin A supplements: A binary measure for whether a child received Vitamin A supplements by a health worker was created based on the following question: "In the last six months, has [NAME] been given Vitamin A supplements by a health worker?" As vitamin A supplements prevent against illnesses and death in children,[70] when administered by a healthcare worker, this is an indicator of healthcare use.

Appendix B3: Sensitivity Analyses for paper 2

Appendix B3.1: Results analyzing outcomes on health card versus self-reported measures[1]

Table B3.1.a: CT-OVC impact on disease specific vaccinations reported on health card

	Received BCG vaccination		**Received Polio vaccination**		**Number of polio vaccinations received**		**Received DPT vaccination**		**Number of DPT received**		**Received Measles vaccination**	
CT-OVC	0.02	0.01	-0.00	0.05	0.12	0.05	0.01	0.01	0.03	0.00	0.03	0.02
	(0.02)	(0.02)	(0.02)	(0.04)	(0.11)	(0.10)	(0.02)	(0.02)	(0.08)	(0.08)	(0.05)	(0.05)
POST	-0.01	-0.00	-0.02	0.04	-0.23**	-0.25**	-0.01	-0.01	-0.16**	-0.18**	-0.13***	-0.16***
	(0.02)	(0.02)	(0.01)	(0.03)	(0.10)	(0.11)	(0.02)	(0.02)	(0.07)	(0.08)	(0.05)	(0.05)
DD	-0.00	-0.01	0.02	-0.03	0.08	0.06	0.01	0.01	0.09	0.07	0.06	0.03
	(0.02)	(0.02)	(0.02)	(0.04)	(0.12)	(0.12)	(0.02)	(0.02)	(0.09)	(0.09)	(0.06)	(0.05)
Observations	1,402	1,401	1,402	2,433	1,402	1,401	1,402	1,401	1,402	1,401	1,402	1,401
R-squared	0.00	0.04	0.00	0.05	0.02	0.10	0.00	0.04	0.01	0.09	0.02	0.17

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

[1] The outcomes in the main analysis that include both health card and self-reported measures are receipt of any BCG vaccination, receipt of any polio vaccination, number of polio vaccinations received, received DPT vaccination, number of DPT vaccinations and receipt of any measles vaccinations.

Table B3.1.b: CT-OVC impact on disease specific vaccinations self-reported

	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.07*	0.06	0.04	0.04	1.01***	0.84***	0.04	0.04	0.05	-0.01	0.00	0.01
	(0.04)	(0.05)	(0.03)	(0.04)	(0.27)	(0.28)	(0.04)	(0.05)	(0.19)	(0.35)	(0.03)	(0.04)
POST	0.08**	0.07	0.04	0.02	0.16	-0.02	0.00	-0.03	-0.14	-0.30	0.02	-0.01
	(0.04)	(0.05)	(0.03)	(0.04)	(0.26)	(0.26)	(0.04)	(0.05)	(0.18)	(0.34)	(0.03)	(0.04)
DD	-0.08*	-0.08	-0.03	-0.03	-0.73**	-0.62*	-0.02	-0.03	-0.05	-0.06	0.01	-0.00
	(0.05)	(0.06)	(0.04)	(0.05)	(0.32)	(0.33)	(0.05)	(0.06)	(0.22)	(0.35)	(0.04)	(0.04)
Observations	1,526	1,526	1,495	1,495	1,117	1,117	1,510	1,510	1,192	1,192	1,280	1,280
R-squared	0.00	0.05	0.00	0.06	0.02	0.21	0.00	0.07	0.00	0.09	0.00	0.08

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.1.c Time preference effect on CT-OVC impact on disease specific vaccinations reported on health card

	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.02	0.02	0.01	0.01	0.18	0.11	0.02	0.02	0.05	0.02	0.04	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.12)	(0.11)	(0.02)	(0.02)	(0.09)	(0.10)	(0.06)	(0.06)
Time Preference	0.02	0.03	0.01	0.01	0.35	0.36***	0.04	0.03*	0.22	0.21**	0.13	0.11
	(0.05)	(0.02)	(0.04)	(0.01)	(0.26)	(0.14)	(0.05)	(0.02)	(0.20)	(0.09)	(0.12)	(0.08)
Post	-0.02	-0.02	-0.02	-0.02	-0.26**	-0.27**	-0.00	0.00	-0.16*	-0.18*	-0.14***	-0.17***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.13)	(0.02)	(0.02)	(0.08)	(0.10)	(0.05)	(0.05)
CTOVC*Post	0.00	-0.00	0.01	0.01	0.12	0.10	-0.01	-0.01	0.13	0.10	0.08	0.06
	(0.03)	(0.02)	(0.02)	(0.02)	(0.14)	(0.14)	(0.02)	(0.03)	(0.11)	(0.11)	(0.07)	(0.06)
CTOVC * Time	-0.08	-0.09	-0.01	-0.00	-0.44	-0.40*	-0.02	-0.03	-0.27	-0.24	-0.08	-0.05
	(0.06)	(0.06)	(0.05)	(0.01)	(0.35)	(0.23)	(0.06)	(0.02)	(0.26)	(0.16)	(0.16)	(0.11)
Time*Post	-0.02	-0.01	0.02	0.02	-0.09	-0.06	-0.04	-0.04	-0.22	-0.24	-0.09	-0.11
	(0.06)	(0.04)	(0.04)	(0.02)	(0.32)	(0.19)	(0.06)	(0.04)	(0.24)	(0.24)	(0.15)	(0.15)
CTOVC * Time * Post	0.02	0.02	-0.01	-0.01	-0.12	-0.13	0.03	0.04	-0.01	-0.00	-0.10	-0.07
	(0.07)	(0.07)	(0.06)	(0.02)	(0.41)	(0.31)	(0.07)	(0.04)	(0.31)	(0.28)	(0.19)	(0.16)
Observations	1,262	1,261	1,262	1,261	1,262	1,261	1,262	1,261	1,262	1,261	1,262	1,261
R-squared	0.01	0.05	0.01	0.03	0.03	0.12	0.00	0.04	0.02	0.11	0.03	0.18

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.1.d: Time preference effect on CT-OVC impact on disease specific vaccinations self-reported

	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.10**	0.10*	0.08**	0.09**	1.11***	0.94***	0.07	0.07	0.06	-0.01	0.02	0.03
	(0.04)	(0.06)	(0.04)	(0.05)	(0.30)	(0.31)	(0.05)	(0.06)	(0.21)	(0.41)	(0.04)	(0.05)
Time Preference	0.15	0.15	0.19*	0.17***	-0.39	-0.31	0.25*	0.24***	-0.31	-0.20	0.14	0.14***
	(0.13)	(0.11)	(0.11)	(0.04)	(0.93)	(0.35)	(0.14)	(0.06)	(0.69)	(0.37)	(0.10)	(0.05)
Post	0.10**	0.08	0.06*	0.04	0.15	0.00	0.03	-0.00	-0.19	-0.37	0.03	0.00
	(0.04)	(0.05)	(0.03)	(0.05)	(0.29)	(0.28)	(0.04)	(0.06)	(0.20)	(0.39)	(0.04)	(0.04)
CTOVC*Post	-0.11**	-0.12*	-0.08*	-0.08	-0.75**	-0.70*	-0.07	-0.08	-0.11	-0.11	0.00	-0.02
	(0.05)	(0.06)	(0.04)	(0.05)	(0.36)	(0.37)	(0.05)	(0.06)	(0.25)	(0.41)	(0.04)	(0.05)
CTOVC * Time	-0.19	-0.18	-0.25**	-0.23**	-0.30	-0.14	-0.28*	-0.27***	-0.28	-0.28	-0.18	-0.12
	(0.15)	(0.14)	(0.13)	(0.09)	(1.09)	(0.55)	(0.16)	(0.10)	(0.79)	(0.49)	(0.12)	(0.09)
Time*Post	-0.17	-0.15	-0.23*	-0.19*	0.01	0.25	-0.28*	-0.23*	0.23	0.42	-0.15	-0.16**
	(0.15)	(0.17)	(0.13)	(0.11)	(1.08)	(0.55)	(0.16)	(0.12)	(0.77)	(0.57)	(0.12)	(0.08)
CTOVC * Time * Post	0.23	0.22	0.34**	0.33**	0.02	-0.07	0.36**	0.32**	0.32	0.09	0.12	0.07
	(0.17)	(0.20)	(0.15)	(0.14)	(1.28)	(0.76)	(0.18)	(0.16)	(0.90)	(0.69)	(0.14)	(0.12)
Observations	1,369	1,369	1,342	1,342	997	997	1,355	1,355	1,066	1,066	1,152	1,152
R-squared	0.01	0.05	0.01	0.07	0.02	0.20	0.00	0.08	0.01	0.10	0.01	0.09

Robust standard errors in parentheses number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.1.e Time preference effect on CT-OVC impact on disease specific vaccinations reported on health card

VARIABLES	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.02	0.02	-0.01	-0.01	-0.00	-0.07	0.00	-0.00	-0.05	-0.09	0.02	0.00
	(0.03)	(0.04)	(0.02)	(0.01)	(0.17)	(0.15)	(0.03)	(0.03)	(0.13)	(0.12)	(0.08)	(0.07)
Risk Preference	0.02	0.01	-0.02	-0.01	-0.17	-0.12	-0.01	0.00	-0.08	-0.04	-0.09	-0.07
	(0.03)	(0.04)	(0.03)	(0.02)	(0.18)	(0.16)	(0.03)	(0.03)	(0.14)	(0.13)	(0.08)	(0.08)
Post	-0.01	-0.01	-0.03	-0.03	-0.33**	-0.34**	-0.01	-0.01	-0.23*	-0.24**	-0.17**	-0.19***
	(0.03)	(0.04)	(0.02)	(0.02)	(0.16)	(0.14)	(0.03)	(0.03)	(0.12)	(0.11)	(0.07)	(0.06)
CTOVC*Post	0.01	-0.00	0.02	0.02	0.27	0.22	0.02	0.02	0.29*	0.25*	0.12	0.07
	(0.04)	(0.04)	(0.03)	(0.02)	(0.20)	(0.18)	(0.03)	(0.04)	(0.15)	(0.14)	(0.09)	(0.07)
CTOVC * Risk	-0.01	-0.01	0.02	0.02	0.21	0.22	0.02	0.03	0.14	0.17	0.02	0.03
	(0.04)	(0.04)	(0.03)	(0.02)	(0.22)	(0.20)	(0.04)	(0.04)	(0.17)	(0.16)	(0.10)	(0.10)
Risk*Post	0.01	0.01	0.02	0.01	0.17	0.14	0.01	-0.00	0.12	0.09	0.07	0.05
	(0.04)	(0.05)	(0.03)	(0.03)	(0.20)	(0.20)	(0.03)	(0.04)	(0.15)	(0.16)	(0.09)	(0.09)
CTOVC * Risk * Post	-0.01	-0.01	-0.01	-0.01	-0.31	-0.28	-0.02	-0.02	-0.31	-0.30	-0.09	-0.06
	(0.05)	(0.05)	(0.04)	(0.03)	(0.25)	(0.24)	(0.04)	(0.05)	(0.19)	(0.19)	(0.12)	(0.10)
Observations	1,402	1,401	1,402	1,401	1,402	1,401	1,402	1,401	1,402	1,401	1,402	1,401
R-squared	0.00	0.04	0.01	0.03	0.02	0.11	0.00	0.04	0.01	0.10	0.02	0.17

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.1.f: Time preference effect on CT-OVC impact on disease specific vaccinations self-reported

VARIABLES	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.05	0.04	0.01	0.01	1.60***	1.20***	0.07	0.07	-0.19	-0.36	-0.01	-0.01
	(0.06)	(0.07)	(0.05)	(0.06)	(0.43)	(0.43)	(0.07)	(0.08)	(0.30)	(0.76)	(0.05)	(0.05)
Risk Preference	-0.08	-0.03	-0.07	-0.02	-0.11	0.35	-0.04	0.03	-0.86***	-0.62	-0.04	-0.03
	(0.06)	(0.08)	(0.06)	(0.06)	(0.45)	(0.38)	(0.07)	(0.08)	(0.31)	(0.74)	(0.05)	(0.06)
Post	0.06	0.06	0.04	0.04	0.53	0.41	0.00	-0.01	-0.56**	-0.63	-0.02	-0.04
	(0.06)	(0.07)	(0.05)	(0.06)	(0.42)	(0.37)	(0.06)	(0.07)	(0.28)	(0.72)	(0.05)	(0.04)
CTOVC*Post	-0.13*	-0.15*	-0.06	-0.08	-1.52***	-1.37***	-0.08	-0.10	0.12	0.14	0.05	0.04
	(0.07)	(0.09)	(0.06)	(0.07)	(0.51)	(0.50)	(0.08)	(0.09)	(0.35)	(0.75)	(0.06)	(0.06)
CTOVC * Risk	0.02	0.04	0.04	0.05	-0.98*	-0.59	-0.06	-0.05	0.39	0.59	0.02	0.03
	(0.08)	(0.10)	(0.07)	(0.08)	(0.55)	(0.55)	(0.09)	(0.10)	(0.38)	(0.78)	(0.07)	(0.07)
Risk*Post	0.03	0.01	-0.01	-0.04	-0.64	-0.73	0.00	-0.03	0.69*	0.58	0.07	0.06
	(0.07)	(0.09)	(0.07)	(0.08)	(0.53)	(0.47)	(0.08)	(0.09)	(0.36)	(0.76)	(0.06)	(0.07)
CTOVC * Risk * Post	0.10	0.12	0.06	0.08	1.33**	1.23*	0.10	0.12	-0.28	-0.33	-0.07	-0.08
	(0.09)	(0.11)	(0.08)	(0.10)	(0.66)	(0.64)	(0.10)	(0.12)	(0.45)	(0.81)	(0.08)	(0.08)
Observations	1,526	1,526	1,495	1,495	1,117	1,117	1,510	1,510	1,192	1,192	1,280	1,280
R-squared	0.01	0.06	0.01	0.07	0.04	0.21	0.00	0.07	0.01	0.10	0.00	0.09

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Appendix B3.2: Results using continuous economic preference measure

Table B3.2.a Time preference effect on CT-OVC impact on general healthcare use

	Has Health card		Weighed by Health Worker		Sought treatment for Diarrhea		Received vitamins from a healthcare worker	
CT-OVC	-0.102	-0.079	0.057	0.041	0.129	0.118	0.124	0.125
	(0.104)	(0.114)	(0.077)	(0.104)	(0.134)	(0.184)	(0.084)	(0.115)
Time Preference	0.025	0.016	0.003	0.002	-0.020	-0.018	0.003	0.001
	(0.020)	(0.023)	(0.015)	(0.017)	(0.028)	(0.039)	(0.016)	(0.023)
Post	0.282***	0.228**	0.126	0.083	0.041	-0.048	-0.062	-0.121
	(0.091)	(0.100)	(0.080)	(0.092)	(0.130)	(0.162)	(0.087)	(0.117)
CTOVC*Post	0.078	0.070	-0.113	-0.100	-0.094	0.023	0.023	0.033
	(0.117)	(0.124)	(0.103)	(0.134)	(0.171)	(0.195)	(0.113)	(0.142)
CTOVC * Time	0.015	0.009	-0.010	-0.010	-0.019	-0.008	-0.036*	-0.040
	(0.025)	(0.028)	(0.019)	(0.025)	(0.035)	(0.046)	(0.021)	(0.028)
Time*Post	-0.038*	-0.028	-0.021	-0.011	0.005	0.017	0.018	0.022
	(0.022)	(0.024)	(0.020)	(0.022)	(0.034)	(0.041)	(0.022)	(0.028)
CTOVC * Time * Post	-0.014	-0.013	0.028	0.023	0.038	-0.001	0.028	0.026
	(0.029)	(0.030)	(0.025)	(0.033)	(0.043)	(0.050)	(0.028)	(0.035)
Observations	2,356	2,355	1,877	1,877	548	548	1,800	1,800
R-squared	0.024	0.119	0.004	0.099	0.027	0.099	0.020	0.063

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.2.b: Time preference effect on CT-OVC impact on disease specific vaccinations

	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.073	0.092	0.074	0.089	0.398	0.546	0.050	0.043	0.019	0.058	0.127	0.122
	(0.072)	(0.079)	(0.062)	(0.074)	(0.355)	(0.345)	(0.080)	(0.087)	(0.331)	(0.340)	(0.096)	(0.120)
Time Preference	-0.006	-0.010	-0.002	-0.009	0.064	0.053	-0.004	-0.012	0.013	-0.005	0.023	0.023
	(0.014)	(0.015)	(0.012)	(0.014)	(0.065)	(0.062)	(0.015)	(0.015)	(0.061)	(0.055)	(0.018)	(0.024)
Post	0.071	0.048	0.083	0.059	0.623**	0.449	0.055	-0.004	0.067	-0.182	-0.000	-0.059
	(0.063)	(0.064)	(0.054)	(0.059)	(0.298)	(0.279)	(0.068)	(0.069)	(0.280)	(0.264)	(0.083)	(0.115)
CTOVC*Post	-0.068	-0.085	-0.089	-0.092	-0.262	-0.277	-0.071	-0.055	-0.087	-0.030	-0.036	-0.037
	(0.081)	(0.085)	(0.070)	(0.079)	(0.396)	(0.386)	(0.090)	(0.089)	(0.367)	(0.325)	(0.108)	(0.128)
CTOVC * Time	-0.005	-0.008	-0.004	-0.004	-0.019	-0.049	-0.001	0.002	-0.022	-0.034	-0.038	-0.039
	(0.018)	(0.020)	(0.015)	(0.018)	(0.086)	(0.084)	(0.019)	(0.021)	(0.080)	(0.076)	(0.023)	(0.028)
Time*Post	-0.004	-0.001	-0.005	-0.001	-0.130*	-0.102	-0.005	0.003	-0.057	-0.017	-0.029	-0.021
	(0.016)	(0.016)	(0.013)	(0.015)	(0.073)	(0.067)	(0.017)	(0.017)	(0.069)	(0.055)	(0.020)	(0.026)
CTOVC * Time * Post	0.004	0.006	0.012	0.012	0.027	0.021	0.009	0.003	0.047	0.019	0.032	0.025
	(0.020)	(0.021)	(0.017)	(0.019)	(0.096)	(0.094)	(0.022)	(0.022)	(0.089)	(0.075)	(0.026)	(0.030)
Observations	2,217	2,216	2,190	2,189	1,936	1,935	2,208	2,207	1,998	1,997	2,007	2,006
R-squared	0.005	0.043	0.007	0.050	0.010	0.093	0.002	0.061	0.002	0.075	0.011	0.142

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.2.c Risk preference effect on CT-OVC impact on general healthcare use

	Has Health card		Weighed by Health Worker		Sought treatment for Diarrhea		Received vitamins from a healthcare worker	
CT-OVC	0.125*	0.077	-0.036	-0.057	-0.007	-0.002	-0.078	-0.102
	(0.068)	(0.082)	(0.055)	(0.070)	(0.105)	(0.141)	(0.061)	(0.088)
Risk Preference	0.001	0.008	-0.013	-0.009	0.010	0.003	-0.006	-0.003
	(0.008)	(0.010)	(0.009)	(0.011)	(0.013)	(0.017)	(0.009)	(0.013)
Post	0.185***	0.173***	0.082*	0.046	0.064	0.024	-0.048	-0.091
	(0.046)	(0.056)	(0.046)	(0.058)	(0.078)	(0.088)	(0.051)	(0.068)
CTOVC*Post	-0.165**	-0.144*	0.003	0.016	0.093	0.099	0.227***	0.253***
	(0.070)	(0.076)	(0.063)	(0.079)	(0.114)	(0.140)	(0.070)	(0.094)
CTOVC * Risk	-0.048***	-0.033*	0.016	0.018	0.019	0.025	0.019	0.021
	(0.015)	(0.017)	(0.013)	(0.016)	(0.023)	(0.028)	(0.014)	(0.020)
Risk*Post	-0.012*	-0.012	-0.009	-0.002	-0.003	-0.005	0.014	0.014
	(0.006)	(0.007)	(0.008)	(0.010)	(0.013)	(0.015)	(0.009)	(0.013)
CTOVC * Risk * Post	0.053***	0.045***	-0.004	-0.008	-0.014	-0.022	-0.028*	-0.033*
	(0.014)	(0.015)	(0.013)	(0.017)	(0.023)	(0.027)	(0.014)	(0.019)
Observations	2,356	2,355	1,877	1,877	548	548	1,800	1,800
R-squared	0.027	0.123	0.004	0.099	0.027	0.100	0.018	0.060

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.2.d: Risk preference effect on CT-OVC impact on disease specific vaccinations

VARIABLES	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.082*	0.072	0.048	0.044	0.333	0.205	0.066	0.039	-0.039	-0.229	-0.009	-0.040
	(0.047)	(0.053)	(0.040)	(0.050)	(0.222)	(0.258)	(0.051)	(0.061)	(0.206)	(0.366)	(0.061)	(0.064)
Risk Preference	-0.007	-0.003	-0.011**	-0.007	-0.061**	-0.044*	-0.007	-0.003	-0.036	-0.028	-0.003	-0.003
	(0.005)	(0.006)	(0.005)	(0.005)	(0.026)	(0.026)	(0.006)	(0.007)	(0.023)	(0.028)	(0.007)	(0.009)
Post	0.092***	0.083**	0.074***	0.070*	0.381**	0.320	0.053	0.028	-0.032	-0.135	-0.070*	-0.111**
	(0.032)	(0.042)	(0.027)	(0.038)	(0.150)	(0.204)	(0.034)	(0.046)	(0.139)	(0.268)	(0.042)	(0.046)
CTOVC*Post	-0.171***	-0.179***	-0.108**	-0.101*	-0.401*	-0.365	-0.116**	-0.104	-0.150	-0.094	0.133**	0.106*
	(0.049)	(0.063)	(0.042)	(0.058)	(0.232)	(0.294)	(0.053)	(0.066)	(0.214)	(0.314)	(0.064)	(0.059)
CTOVC * Risk	-0.009	-0.004	0.003	0.008	-0.004	0.045	-0.007	0.002	-0.010	0.044	-0.002	0.004
	(0.010)	(0.012)	(0.009)	(0.011)	(0.048)	(0.054)	(0.011)	(0.013)	(0.044)	(0.049)	(0.013)	(0.015)
Risk*Post	-0.010**	-0.011**	-0.003	-0.005	-0.068***	-0.069***	-0.004	-0.006	-0.032*	-0.031	-0.010*	-0.007
	(0.004)	(0.005)	(0.004)	(0.004)	(0.021)	(0.027)	(0.005)	(0.005)	(0.019)	(0.019)	(0.006)	(0.007)
CTOVC * Risk * Post	0.034***	0.032**	0.018**	0.015	0.071	0.046	0.022**	0.017	0.070	0.038	-0.012	-0.012
	(0.010)	(0.013)	(0.009)	(0.011)	(0.047)	(0.057)	(0.011)	(0.013)	(0.043)	(0.045)	(0.013)	(0.012)
Observations	2,217	2,216	2,190	2,189	1,936	1,935	2,208	2,207	1,998	1,997	2,007	2,006
R-squared	0.014	0.055	0.012	0.055	0.013	0.096	0.004	0.064	0.005	0.078	0.013	0.141

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Appendix B3.3: Weighted regressions

Table B3.3.a Time preference effect on CT-OVC impact on general healthcare use (weighted regressions)

	Has Health card		Weighed by Health Worker		Sought treatment for Diarrhea		Received vitamins from a healthcare worker	
CT-OVC	0.140	-0.0131	-0.192**	-0.0285	-0.152	-0.0408	0.0626	0.00118
	(0.135)	(0.0510)	(0.0805)	(0.0729)	(0.0959)	(0.0436)	(0.0624)	(0.0371)
Time Preference	0.456***	0.321***	-0.646***	-0.504***	-0.160	-0.0335	0.0501	0.0279
	(0.155)	(0.0907)	(0.193)	(0.174)	(0.141)	(0.103)	(0.110)	(0.106)
Post	0.286**	0.329***	-0.158*	-0.227**	-0.160	-0.0717	0.102	0.0381
	(0.131)	(0.0514)	(0.0810)	(0.0924)	(0.101)	(0.0512)	(0.0647)	(0.0451)
CTOVC*Post	-0.137	-0.00784	0.306***	0.169*	0.279***	0.159***	-0.0638	-0.000417
	(0.135)	(0.0565)	(0.0979)	(0.0873)	(0.106)	(0.0582)	(0.0713)	(0.0508)
CTOVC * Time	-0.552***	-0.368***	0.860***	0.796***	0.0297	-0.0745	-0.0223	0.0201
	(0.177)	(0.119)	(0.211)	(0.201)	(0.155)	(0.122)	(0.126)	(0.121)
Time*Post	-0.431***	-0.263**	0.378	0.270	0.188	0.0492	-0.219	-0.153
	(0.164)	(0.110)	(0.248)	(0.223)	(0.177)	(0.147)	(0.134)	(0.129)
CTOVC * Time * Post	0.584***	0.388***	-0.599**	-0.642**	-0.129	-0.00637	0.143	0.0672
	(0.188)	(0.137)	(0.269)	(0.253)	(0.196)	(0.170)	(0.158)	(0.153)
Observations	2,355	2,355	548	548	1,800	1,800	1,877	1,877
R-squared	0.054	0.276	0.069	0.201	0.023	0.110	0.011	0.133

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.3.b: Time preference effect on CT-OVC impact on disease specific vaccinations (weighted regressions)

	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.330*	0.124***	0.338*	0.127***	1.353*	0.595***	0.322*	0.107**	0.765	0.0594	-0.0177	-0.00808
	(0.190)	(0.0360)	(0.189)	(0.0350)	(0.694)	(0.170)	(0.182)	(0.0434)	(0.632)	(0.361)	(0.0454)	(0.0410)
Time Preference	0.424**	0.217***	0.413**	0.190***	1.675**	0.950***	0.442**	0.236***	1.160*	0.510	0.104*	0.112*
	(0.190)	(0.0337)	(0.189)	(0.0321)	(0.723)	(0.235)	(0.181)	(0.0383)	(0.642)	(0.319)	(0.0581)	(0.0588)
Post	0.308*	0.179***	0.313*	0.167***	1.089	0.490***	0.290	0.148***	0.632	0.120	-0.0901**	-0.139***
	(0.186)	(0.0355)	(0.185)	(0.0353)	(0.673)	(0.177)	(0.178)	(0.0426)	(0.619)	(0.368)	(0.0425)	(0.0491)
CTOVC*Post	-0.320*	-0.127***	-0.311*	-0.106***	-1.174*	-0.424**	-0.299*	-0.103**	-0.697	-0.0274	0.0869*	0.0688
	(0.187)	(0.0380)	(0.185)	(0.0370)	(0.681)	(0.185)	(0.179)	(0.0452)	(0.624)	(0.356)	(0.0506)	(0.0474)
CTOVC * Time	-0.492**	-0.279***	-0.448**	-0.224***	-2.284***	-1.307***	-0.480**	-0.268***	-1.461**	-0.633	-0.127	-0.110
	(0.199)	(0.0703)	(0.195)	(0.0615)	(0.779)	(0.336)	(0.193)	(0.0719)	(0.685)	(0.404)	(0.0966)	(0.0884)
Time*Post	-0.422**	-0.207***	-0.397**	-0.185***	-1.719**	-0.996***	-0.444**	-0.246***	-1.100*	-0.306	-0.0778	-0.104
	(0.190)	(0.0550)	(0.188)	(0.0510)	(0.727)	(0.293)	(0.184)	(0.0611)	(0.654)	(0.452)	(0.0829)	(0.0853)
CTOVC * Time * Post	0.464**	0.255***	0.473**	0.269***	2.161***	1.266***	0.523***	0.315***	1.290*	0.310	-0.0231	-0.00948
	(0.202)	(0.0892)	(0.196)	(0.0760)	(0.791)	(0.405)	(0.198)	(0.0918)	(0.703)	(0.519)	(0.115)	(0.112)
Observations	2,216	2,216	2,189	2,189	1,935	1,935	2,207	2,207	1,997	1,997	2,006	2,006
R-squared	0.098	0.308	0.129	0.364	0.084	0.273	0.086	0.283	0.026	0.179	0.013	0.134

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.3.c: Risk preference effect on CT-OVC impact on general healthcare use (weighted regressions)

	Has Health card		**Weighed by Health Worker**		**Sought treatment for Diarrhea**		**Received vitamins from a healthcare worker**	
CT-OVC	0.0189	0.00331	0.0374	0.108	-0.135*	-0.135**	-0.0533	-0.0667
	(0.0807)	(0.0856)	(0.130)	(0.125)	(0.0692)	(0.0660)	(0.0688)	(0.0632)
Risk Preference	-0.262*	-0.0199	0.335***	0.200*	0.0796	-0.0284	-0.180**	-0.0993
	(0.156)	(0.0910)	(0.123)	(0.121)	(0.126)	(0.0698)	(0.0839)	(0.0667)
Post	0.0926	0.294***	0.112	-0.0237	-0.0443	-0.0650	-0.0389	-0.0384
	(0.0816)	(0.0862)	(0.128)	(0.124)	(0.0785)	(0.0756)	(0.0837)	(0.0741)
CTOVC*Post	0.0799	-0.0359	-0.157	-0.0766	0.000872	0.144*	0.162*	0.111
	(0.165)	(0.102)	(0.150)	(0.148)	(0.133)	(0.0824)	(0.0930)	(0.0760)
CTOVC * Risk	0.0799	-0.0359	-0.157	-0.0766	0.000872	0.144*	0.162*	0.111
	(0.165)	(0.102)	(0.150)	(0.148)	(0.133)	(0.0824)	(0.0930)	(0.0760)
Risk*Post	0.221	0.0310	-0.271*	-0.165	-0.147	-0.0154	0.143	0.0862
	(0.159)	(0.0989)	(0.149)	(0.139)	(0.143)	(0.0916)	(0.105)	(0.0856)
CTOVC * Risk * Post	-0.0225	0.0980	0.101	0.0479	0.0783	-0.0824	-0.140	-0.0938
	(0.170)	(0.112)	(0.178)	(0.170)	(0.154)	(0.108)	(0.117)	(0.0994)
Observations	2,607	2,607	633	633	1,992	1,992	2,073	2,073
R-squared	0.057	0.265	0.060	0.163	0.020	0.102	0.015	0.131

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Table B3.3.d: Risk preference effect on CT-OVC impact on disease specific vaccinations (weighted regressions)

VARIABLES	Received BCG vaccination		Received Polio vaccination		Number of polio vaccinations received		Received DPT vaccination		Number of DPT received		Received Measles vaccination	
CT-OVC	0.0169	-0.00312	0.0167	0.00241	0.0968	-0.0253	-0.00465	-0.0207	-0.856	-0.913	-0.0760*	-0.0810*
	(0.0473)	(0.0500)	(0.0430)	(0.0456)	(0.234)	(0.232)	(0.0470)	(0.0522)	(0.810)	(0.801)	(0.0428)	(0.0443)
Risk Preference	-0.345*	-0.0605	-0.357*	-0.0662	-1.489**	-0.407*	-0.385**	-0.100*	-2.034**	-1.182	-0.103*	-0.102**
	(0.207)	(0.0525)	(0.206)	(0.0504)	(0.745)	(0.245)	(0.196)	(0.0589)	(0.962)	(0.756)	(0.0530)	(0.0497)
Post	0.0353	0.132***	0.0435	0.124***	0.0238	0.270	-0.0156	0.0649	-0.945	-0.655	-0.162***	-0.204***
	(0.0405)	(0.0471)	(0.0380)	(0.0451)	(0.203)	(0.235)	(0.0405)	(0.0516)	(0.806)	(0.783)	(0.0397)	(0.0458)
CTOVC*Post	-0.0877*	-0.0815	-0.0543	-0.0445	-0.180	-0.0951	-0.0183	-0.0172	0.788	0.806	0.163***	0.155***
	(0.0513)	(0.0526)	(0.0463)	(0.0479)	(0.252)	(0.246)	(0.0516)	(0.0557)	(0.814)	(0.794)	(0.0544)	(0.0554)
CTOVC * Risk	0.312	0.114*	0.331	0.125**	1.158	0.618**	0.332*	0.135*	1.792*	1.360*	0.0668	0.0866
	(0.210)	(0.0651)	(0.209)	(0.0608)	(0.765)	(0.299)	(0.200)	(0.0716)	(0.971)	(0.794)	(0.0697)	(0.0648)
Risk*Post	0.290	0.0335	0.286	0.0192	1.072	0.104	0.323*	0.0624	1.837*	1.069	0.111*	0.112*
	(0.202)	(0.0548)	(0.201)	(0.0542)	(0.729)	(0.261)	(0.192)	(0.0635)	(0.958)	(0.749)	(0.0644)	(0.0591)
CTOVC * Risk * Post	-0.196	0.00945	-0.228	-0.0158	-0.796	-0.189	-0.241	-0.0378	-1.580	-1.110	-0.124	-0.136*
	(0.206)	(0.0691)	(0.204)	(0.0651)	(0.755)	(0.321)	(0.197)	(0.0770)	(0.970)	(0.787)	(0.0814)	(0.0764)
Observations	2,462	2,462	2,433	2,433	2,156	2,156	2,452	2,452	2,224	2,224	2,225	2,225
R-squared	0.103	0.287	0.136	0.337	0.094	0.261	0.093	0.252	0.068	0.183	0.010	0.130

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controlling for child's age, caregiver age, caregiver education, caregiver marital status, household size, number of rooms, clinic fees, mobile clinic availability, distance to nearest health facility and district

Appendix B4: Data check using healthcare card as an example

	n	probability
Overall:		
CT-OVC=0, POST=0	219	0.5662
CT-OVC=0, POST=1	781	0.717
CT-OVC=1, POST=0	365	0.526
CT-OVC=1, POST=1	1428	0.6926
Time preference=1:		
CT-OVC=0, POST=0	**17**	**0.8235**
CT-OVC=0, POST=1	54	0.6481
CT-OVC=1, POST=0	43	0.4651
CT-OVC=1, POST=1	166	0.741
Time preference=0:		
CT-OVC=0, POST=0	174	0.5402
CT-OVC=0, POST=1	646	0.7136
CT-OVC=1, POST=0	287	0.5331
CT-OVC=1, POST=1	1121	0.6851

In the table above, the interaction of time preference=1, CT-OVC=0 and POST=0 is driven by a small sample size (n=17) yet the probability of having a healthcare card is the highest 0.8235. This is the pattern with all the outcomes (receiving a BCG, polio or flu vaccination) where the n is small (all have n=14 for that particular interaction and it is the same individuals).

APPENDIX C

Appendix C1: Replication of prior analysis examining the effectiveness of the CT-OVC

The original effectiveness study reported using a 3-level GLLAMM model using adaptive quadrature with 12 numerical integration points (nips).[15] Based on these specifications, our GLLAMM could not converge and this could be due to differences in other specifications of the gllamm command in stata that the authors may have ran. The GLLAMM model presented here only specifies the link as logit. We obtain an odds ratio of 0.535 (95% CI 0.336-0.851) compared to the reported 0.556. Despite the slight difference in the odds ratio, the confidence intervals we estimate (95% CI 0.336-0.851) overlap the 0.556 odds ratio. The difference in odds ratio is due to the specification of the -gllamm- command in stata that the authors may have used but was not provided in the published manuscript.

Table C1: Three-level GLAMM model, CT-OVC on pneumonia/malaria in children

	Pneumonia/ Malaria	Standard errors
Treatment effect	**0.535*** **	**(0.127)**
Year	1.242	(0.253)
Treatment status	1.975*	(0.808)
Ref: Age: 5 – 7 years		
Age: under 1 year	1.734*	(0.493)
Age: 1 – under 3 years)	1.792***	(0.335)
Age: 3 – under 5 years	1.079	(0.162)
Sex of child	0.855	(0.113)
Orphan status	0.852	(0.132)
Child/Grandchild	0.836	(0.227)
Female household head	0.904	(0.154)
Age of household head	0.991**	(0.00407)
Household head education	1.009	(0.0195)
Rural	1.423	(0.324)
Mosquito net	0.969	(0.152)
Unprotected/open water source	1.297	(0.206)
Poor cook fuel quality	1.234	(2.099)
Crowding index	0.947	(0.0333)
Asset/wealth index	0.939	(0.0614)
Food insecurity	1.384**	(0.229)
Food expenditures	1.000	(0.000104)
Food variety	1.041*	(0.0225)
Constant	0.853	(1.542)
Observations	1,842	

Appendix C2: Summary of debate on analytical decisions, discussion of proposed approach's and justification for decisions

Analytical Decision	**Debate**	**Proposed approach (including advantages and disadvantages)**	**Decision and justification**
Study perspectives	The **WHO guide to cost-effectiveness** recommends that the societal perspective be included.[123] The **US panel on cost-effectiveness** recommends conducting cost-effectiveness studies from both the health care perspective and from the society perspective.[191]	The perspectives upon which a CEA analysis can be conducted: 1. The healthcare perspective involves the viewpoint from the formal medical sector[191] 2. The society perspective includes the view point that includes all costs and health effects no matter who incurs them.[191]	I conduct the study from the societal and healthcare perspective. I conduct this study from the societal perspective based on recommendations and because there are patients' costs associated with receiving the CT-OVC and the status quo that need to be taken into account to fully assess the economic costs and consequences. I also include the healthcare perspective costs because of the relevance to policy makers that fund social protection programs.
Addressing missing data	If the probability that a value is missing is correlated with certain determinants, this can lead to estimation bias.[123]	Approach to address missing data: 1. Missing data can be imputed if data is not missing in a systematic way.[123]	I assess whether the differences between the study sample and the excluded sample are statistically significant differences between treatment and control groups. If there is not statistical difference, it is unlikely that the

			study sample will be biased.
Cost components (direct versus indirect costs)	Direct costs include health-related costs. Indirect costs are health-unrelated costs and capture the real cost of the disease and real efforts to prevent the disease.[123] According to the **WHO guide to cost effectiveness**, recommends including both direct and indirect costs.[123] The **US panel on cost-effectiveness** recommends including both indirect and direct cost.[191]	-	I include both direct and indirect costs.
Approach for price level	As domestic price levels are usually higher than world market prices in almost all economies, it is important to bring resources into a common basis so as to aggregate them into a cost estimate for a health intervention.[123] This involves choosing a price-level (domestic or world market price) and a currency (national or domestic).[123] The **WHO guide to cost-effectiveness** recommends that the world price is the most appropriate starting point as these prices represent the terms upon which a country can trade.[123] This means that internationally traded goods are valued at their traded prices or "international prices", representing how much foreign-exchange a country gave up to purchase these goods.[123] Non-tradable goods are subject to local market conditions and the international prices may not reflect the true opportunity costs. The recommendation to use international prices is also for	-	I will use the world market price or international price level as this facilitates comparison from studies across different settings. In addition, as this study includes tradable goods, the international price reflects the true opportunity cost for obtaining these goods.

	comparability purposes.[123] The **US second panel on cost-effectiveness in health and medicine** has no recommendations on approach to price level.[124] Although, further recommendation is that studies done in a country should reflect prices for their own setting, and other research from a different setting should adjust this price as is relevant for their own setting.[154]		
Tradable versus non-tradable goods	The **WHO guide to cost-effectiveness** recommends valuing traded goods in international prices and non-traded goods in local market prices when price and cost information is not available from their study setting. Doing this will reflect the true opportunity costs to a country by accounting for the tradable and non-tradable goods that cannot simply be aggregated by taking these prices at face value. This involves revaluing non-tradable goods to international prices while traded goods will be adjusted to include the cost, insurance and freight for imported goods.[123] Non-traded goods should be valued using the purchasing power parity (PPP) The **US second panel on cost-effectiveness in health and medicine** has no recommendations on approach to treating tradable and non-tradable goods.[124]	Methods for valuing tradable and non-tradable goods into a common basis: 1. Traded goods should be valued as they are in international prices and non-traded goods should be converted using the purchasing-power parity (PPP).[154] The international price for traded goods should be used if there is no reason to believe the price would vary in that country.[154] Variation may include for instance availability of a generic drug or domestic transport costs.	I will distinguish between tradable and non-tradable goods. Tradable goods include medications and equipment, while non-tradable goods include labor patient and transportation costs. I will use the international price of the traded goods as there is no reason to believe the prices would vary in Kenya – for instance, it is unlikely that there is a generic drug available in Kenya. I will use the PPP for non-traded goods.
Currency choice	The **WHO guide to cost-effectiveness** recommends that studies done in a country	The following are the reporting currency choices and advantage and disadvantages:	I report costs in US ($) to allow for

	should report costs in the local currency as other researchers can convert the estimates from their study to that which is relevant to them.[123] The **US second panel on cost-effectiveness** only recommends that the type of currency should be stated.[124]	1. International dollars: The international dollars are a hypothetical currency used to translate and compare costs from one country to another. Therefore, it allows for comparability with other studies as it captures the difference in purchasing power.[123] However, the fact that this is a hypothetical currency means it may not be that meaningful when contextualizing the results of the study 2. US ($): The advantage of using is that it is a commonly used international currency. Reporting in US$ may be relevant for donors.[154] 3. Local currency: Local currency is relevant for local policy makers.[154] However, it limits comparability to other studies	comparability with other studies and for the ease of contextualizing the findings.
Year for reporting costs	It is recommended to inflation adjust to the year in which the results will be reported.[155]	-	I choose to report costs based on the most recent year with GDP deflator from the World Bank is available.[156]
Inflation adjustment	When the costs in the study are obtained from different time periods, it is important to adjust for inflation. The **WHO guide to cost-effectiveness** recommends using the health component of the (Gross Domestic Product) GDP deflator.[123] When that is not available the GDP deflator should be used. If the GDP deflator is not available, the Consumer Price Index (CPI) should be used. The CPI is only	The approaches for inflation adjustment are as follows: 1. Gross Domestic Product (GDP) deflator. The GDP deflator is the price index that measures the change in the price level compared to real output.[123] The advantage of the GDP deflator incorporates all aspects of the economy and the annual price change.[123]	I select the GDP deflator as this is the recommended by the WHO. It is also the only available index for Kenya.

	appropriate if the price in question is changing at the rate of the general price inflation.[123] The **US panel on cost-effectiveness** states that there is no gold standard for inflation adjustment.[191]	2. Consumer Price Index (CPI). The CPI reflects the change in the cost of the average consumer purchasing a fixed basket of goods and services.[123] The advantage is that the CPI is a commonly used measure that can be generated for specific commodities.[155,191] The CPI includes a medical component that can be used to adjust for medical health services.[155] The disadvantage is that the CPI medical component is not available for Kenya. It is also questionable if the choice of goods and services in the basket reflects health costs as a whole.[123] 3. Personal Consumption Expenditure (PCE). The PCE reflects all personal expenditure, such as medical expenditure.[192] However, the PCE does not include government investments and expenditures.[192] It is also not available for Kenya 4. Personal HealthCare (PHC) Expenditure is proposed for disease-specific costs	
Order for inflation adjustment and exchange rate calculations	The **WHO** recommends adjusting for inflation and then applying the exchange rate[154]	The order for inflation adjustment and exchange rate: 1. Inflation adjust and then apply the exchange rate	I adjust for inflation before applying the exchange rate
Discount rates for health effects	The **WHO-CHOICE** recommends a discount rate of 3% and a rate of 6% in the sensitivity analysis.[123]	-	I discount health effects using a discount rate of 3%
Discount rate for costs	Discounting is the process of converting future cost to their present value.[123]	-	I discount costs at a rate of 3%

	The US Panel on cost-effectiveness recommends valuing costs at the same rate as the health effects.[191]		
Confidence intervals for ICER	The confidence intervals for cost-effectiveness ratios provide probabilistic values within which one can be confident that the true ratio lies.[155] There is no recommendation from the **WHO guide to cost-effectiveness** or from the **US panel on cost-effectiveness** on which approach to use for estimating the confidence intervals.	The approaches to estimating confidence intervals:[155] 1. Nonparametric bootstrap methods: This involves creating replications of the statistic of interest by sampling and replacing the original data. 1.1 Bootstrap percentile method: This method uses ordered replicates to identify a confidence interval 1.2 Bootstrap acceptability method: This method does not involve ordering of the replicates This method does not require any assumption about the distribution of the ratio.[193] 2. Fiellers method: This method is based on the assumption that the difference in the arithmetic mean effect and the arithmetic mean cost has a normal distribution.[155] This method assumes the numerator and denominator follows a bivariate normal distribution.[193] The Fiellers method takes into account the skewness of the data.[193] However, depending on the rigor of non-parametric bootstrap, the confidence intervals produced are similar to those from a parametric method.[193]	I use nonparametric bootstrap method to estimate the confidence intervals for the ICER
Performance of the CCT (Willingness-to-pay (WTP) threshold)	The **WHO Choosing Interventions that are Cost-Effective or WHO-CHOICE** recommends a WTP threshold of three times	-	I use a WTP threshold of 3 times the GDP per-capita and a threshold

	the per-capita GDP.[159] One times the per-capita GDP is considered to be highly cost-effective.[159]		of once the GDP per capita for the CT-OVC to be highly cost-effective.

Appendix C3: Variable definition in model on effectiveness

Variable	Definition
Post	1= post-baseline period; 0=baseline period
Treatment status	1= child is in household that received CT-OVC vs 0=not in CT-OVC household
Age	Age of child (under 1 year, 1-2 years, 3-4 years, 5-7 years)
Male child	1= male child; 0=female child
Orphan status	1= child is orphan; 0= child is not an orphan
Child/Grandchild	1= child is the son/daughter/grandchild of the household head; 0= child is not the son/daughter/grandchild of the household head
Female household head	1= female household head; 0=male household head
Age of household head	Continuous variable for age of household head
Household head education	1= household head has more than high school; 0= less than high school
Rural	1= household in rural area; 0= household not in rural area
Mosquito net	1=household owns a mosquito net; 0= household does not own a mosquito net
Unprotected/open water source	1= Households that did not source their drinking water from natural sources obtained water via pipes into the dwelling or compound, public outdoor tap or borehole with a pump, protected well or spring, mobile vendor, or purchased from a neighbor 0=natural sources of water
Poor cook fuel quality	1= Households that used paraffin, kerosene, firewood, charcoal, residue, animal waste, or grasses were coded as using poor cook fuel. 0=Acceptable cook fuels included electricity and gas
Crowding index	Ratio of household size to number of rooms
Food insecurity	1= low food availability in the community; 0=higher food availability in the community
Food expenditure	Amount of money spent on a variety of food items
Food variety	Total number of different foods consumed
Season	Count variable for the month of the year

Appendix C4: Review of statistical models to estimate treatment effect in cluster-randomized trials with binary outcome

Approach	Advantages	Disadvantages
Generalized Estimating Equations (GEE)	The GEE estimates the change in the population mean given changes in the covariates while accounting for within neighborhood dependence.[158] This approach eliminates the need for determining the link and family.[155] The population average model provides a more relevant approximation of the truth.[158]	The GEE is not recommended for cluster-randomized trials with few clusters (less than 20 clusters across treatment groups).[194,195]
Logistic Regression	Commonly used and widely acceptable	Does not permit multiple levels of clustering[15]
Generalized Linear Latent and Mixed Models (GLLAMM)	Allows for nesting of hierarchical data when levels are expected to influence outcomes.[15]	Requires assumptions that cannot be tested by the data.[158] The Stata command has not been updated since 2004 and may not work well with newer versions of Stata
Generalized Linear Model (GLM)	Model both the mean and variance on the original cost data.[155] The GLM relaxes the OLS assumption of linearity and homoskedasticity.[155] To estimate the arithmetic mean involves simply exponentiating the predicted results.[155] The GLM with a gamma distribution is robust to violations of distributional assumptions.[155] The GLM model can be extended to account for nested data	Misspecification of the family (that is, guassian, poisson or gamma) lead to a loss in efficiency, however, the estimates will be correctly specified.[155] The correct family can be specified using a Parks test.[155] There is no test to specify the correct link function, which can result in bias of the results.[155]

I select to use the Generalized Estimating Equation (GEE) as the model provides population average estimates and does not require distributional assumptions. Further, this study has 28 clusters and the GEE model will work well on the data.

Appendix C5: Statistical methods for estimating incremental costs

Approach	Advantages	Disadvantages
Generalized Linear Models (GLM)	The GLM models both the mean and variance on the original cost data.[155] The GLM relaxes the OLS assumption of linearity and homoskedasticity.[155] Modelling with a log link differs from the OLS on log-transformed because it models the log of the arithmetic mean as opposed to the arithmetic mean of log-cost.[155] To estimate the arithmetic mean involves simply exponentiating the predicted results.[155] The GLM with a gamma distribution is robust to violations of distributional assumptions.[155]	Misspecification of the family (that is, guassian, poisson or gamma) lead to a loss in efficiency, however, the estimates will be correctly specified.[155] The correct family can be specified using a Parks test.[155] There is no test to specify the correct link function, which can result in bias of the results.[155]
Generalized Estimating Equations (GEE)	Estimates the population mean and does not require distributional assumptions.[158] This approach eliminates the need for determining the link and family.[155] The population average model provides a more relevant approximation of the truth.[158]	The GEE is not recommended for cluster-randomized trials with few clusters (less than 20 clusters across treatment groups).[194,195]
Multilevel Models (MLM)	Allow for the correlation of costs and recognize clustering.[195] Assumes a normal distribution on the error term.[195]	The model may fail to converge if there are few individuals in a cluster.[195] This model assumes an unverifiable assumption of the data-generating distribution that can lead to misleading estimates and biased inferences.[158]
Ordinary least squares (OLS) regression with log-transformed costs	The transformed cost data may have a normal distribution and this assumption for the OLS to produce efficient estimates may not be violated.[155]	The estimates and inferences made about the log-transformed estimate may not apply to the arithmetic mean.[155] The retransformation requires homoskedasticity.[155]
Ordinary least squares (OLS) regression on untransformed costs	The OLS model is easy to implement and readily understood.[155]	As healthcare cost data often violate the assumptions of OLS (normality), the variance of the estimate is affected.[155] Further, the model results will be prone to highly skewed data.[155]
Sample/arithmetic mean: The difference in sample mean costs between treatment and control	This measure is simple measure that informs policy-makes on cost of adopting an intervention.[155]	There is limited power of the tests in differences between treatment and controls.[155] Further, it does not account for differences in economic conditions or subgroups.[155]

I select to use the Generalized Estimating Equation (GEE) as the model provides population average estimates and does not require distributional assumptions. Further, this study has 28 clusters and the GEE model will work well on the data.

Appendix C6: Sensitivity analysis

Table C6: Cost-effectiveness for complete case analysis

	Healthcare perspective		**Societal perspective**	
	Estimate	95% CI*	Estimate	95% CI*
Incremental effectiveness (DALYs averted)	0.002	[0.002 – 0.002]	0.002	[0.002 – 0.002]
Incremental cost (US$)	376.23	[363.34-389.12]	763.90	[737.77 – 790.04]
ICER	**177,009**	**[158,243-195,776]**	**359,403**	**[317,356 - 401,451]**

Abbreviations: CI, confidence intervals; DALYs, disability adjusted life years; ICER, incremental cost-effectiveness ratio; US$, United States Dollars *95% CI generated using the bootstrap method

CURRICULUM VITAE

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Profile

- **Skills**: Quasi-experimental methods; Econometric Modelling; Cost-Effectiveness Analysis; Survey, panel and insurance claims data analysis
- **Computer skills**: Stata, SAS, R, SPSS, Arc GIS, MS Word, MS Excel

Education

VIRGINIA COMMONWEALTH UNIVERSITY, Doctor of Philosophy (August 2017 – July 2021)

- **Dissertation**: Policies addressing barriers to low-income women and children's health care utilization in Kenya and the United States: The role of cash transfer programs and physician payments
- **Relevant coursework**: Health Economics, Econometrics, Economic Evaluation and Decision Analysis, Panel Methods, Epidemiology Methods, Applied Health Policy, Statistical Methods,

UNIVERSITY OF CAPETOWN, Master of Commerce in Applied Economics (January 2011 - June 2013)

- **Relevant coursework**: Advanced Econometrics, Advanced Microeconomics, Macroeconomic Policy Analysis, Advanced Macro Economics, Time Series Analysis

UNIVERSITY OF NAMIBIA, Bachelor of Economics (January 2007 - December 2010)

Professional Experience

WORLD BANK- Washington DC (January 2021 – present)
Consultant/Africa-Fellow

- Contribute to the work international development as part of the COVID-19 SWAT team supporting East African Region
- Conduct economic assessment related with the response of the pandemic giving priority to COVID-19 vaccination programs in Malawi
- Supporting Malawi and South Sudan teams in developing proposals for ESMAP funding
- Conducting climate risk and disaster screens for the Additional Finance COVID-19 vaccination rollout programs
- Supporting country teams with climate co-benefits and gender tagging of the project paper documentation - supporting Zambia, Ethiopia, ESwatini, Malawi and South Sudan
- Developing a proposal to assess COVID-19 vaccine hesitancy and its correlates in East Africa region

PHARMERIT INTERNATIONAL- Maryland, Bethesda (October 2020 – January 2021)
Health Economics and Outcomes Research Fellow

- Design and construction of health economic models and programming (budget impact and Markov models)
- Health Economics and Outcomes Research writing, developing manuscripts and abstracts of technical reports such as claims database analysis and economic models

CIVIL SOCIETY FOR POVERTY REDUCTION - Zambia (April 2015 – June 2017)
Program Manager

- Led a team of program officers and provincial coordinators and successfully conducted budget tracking and service delivery monitoring to improve public service delivery in rural communities
- Developed budget tracking tools and service delivery monitoring tools and conducted capacity building of community members to conduct social accountability activities and advocate for their rights to local leaders
- Revised the institutions strategic plan to enhance collaboration with CSPR cooperating partners and the institutions network members of Civil Society Organizations (CSO)
- Raised over $100,000 of institutional funding through grant writing
- Collaborated with international agencies, including Norwegian Church Aid, USAID and UNICEF, and managed project budgets and fulfilled all reporting requirements

LONDON SCHOOL OF ECONOMICS' INTERNATIONAL GROWTH CENTER- Zambia (March 2013 – March 2015)
Country Economist

- Conducted research for the Zambia Revenue Authority on redesigning the property taxation policy
- Conducted high-level stakeholder meetings and successfully represented IGC Zambia in London
- Developed country research priorities in consultation with the Government of Zambia and liaised with international experts to increase their collaboration with the Zambian government on country research priorities

SOUTHERN AFRICA LABOR AND RESEARCH UNIT South Africa (January 2011– February 2013)
Data Cleaner and Analysts

- Conducted data analysis on the first national panel survey in South Africa and contributed to the successful release of the third wave of data
- Data quality control of the data collected by survey data collectors

Research and Teaching Experience

VIRGINIA COMMONWEALTH UNIVERSITY – Richmond, VA (August 2017 – September 2020)
Graduate Research Assistant

- Conducting analyses using quasi-experimental methods to examine Medicaid expansion impacts on maternal health behaviors (maternal weight and smoking)
- Conducting analyses for behavior economics research assessing the demand for cigar using a hypothetical purchasing task
- Conducted the analysis and drafted manuscripts on the quality of colonoscopies; immigrant health, pregnancy-related weight, and the Earned Income Tax Credit
- Data analysis, writing manuscripts, develop and conduct statistical and econometric modeling, and conducting literature reviews

VIRGINIA COMMONWEALTH UNIVERSITY – Richmond, VA (August 2019 – December 2020)
Graduate Teaching Assistant in Introduction to Health Policy

- Facilitate class discussions, select relevant class readings, and grade midterm and final exams for Master's in Public Health students
- Organize guest lectures featuring several researchers and health policy experts

Publications in Peer-Reviewed Journal

Muloongo Simuzingili, William Garner, Caroline Cobb, Andrew Barnes. *"What Influences Demand for Cigars among African American Adult Cigar Smokers? Results from a hypothetical purchase task"*

Tiffany Green Ph.D, Yena Son, **Muloongo Simuzingili MCom**, Briana Mezuk Ph.D, Mandar Bodas Ph.D, Michelle Vargas Ph.D, and Nao Hagiwara Ph.D (2020). "*Pregnancy-Related Weight and Postpartum Depressive Symptoms: Do the relationships differ by race/ethnicity*?" Journal of Maternal Health

Tiffany Green Ph.D, **Muloongo Simuzingili MCom,** Mandar Bodas Ph.D, Hong Xue Ph.D, "*Pregnancy-Related Weight among Immigrant and US-born Mothers: The Role of Nativity, Maternal Duration of Residence, and Age at Arrival.*" Journal of Women's Health

Publications – Submitted to Journal and Under-review

- Tamala Gondwe Ph.D, **Muloongo Simuzingili, MCom**, Tiffany Green, Ph.D. "*Source of Prenatal Care and Non-Receipt of Postpartum Healthcare in the United States*" Journal of Women's Health.
- Askar Chukmaitov M.D, Ph.D, Bassam Dahman Ph.D, Yangyang Deng M.S, M.P.H., **Muloongo Simuzingili, MCom**, Shiva Salehian M.D., Dennis Tsilimingras, M.D, "*Colonoscopy Quality or Annual Colonoscopy Volume: What is More Important for Polyp and Adenoma Detection*?" Journal of Diseases of Colon and Rectum.

Working Papers (First Author)

- **Muloongo Simuzingili**, Tia Palermo, David Harless, April Kimmel, Andrew Barnes. *"Do Economic Preferences moderate cash transfer program effects on children's health care utilization? Evidence from a randomized field experiment in Kenya"*
- **Muloongo Simuzingili**, April Kimmel, Tia Palermo, David Harless, Andrew Barnes. *"Are cash transfer programs cost-effective in reducing Pneumonia and Malaria amongst children in Kenya"*
- **Muloongo Simuzingili**, Todd Hamilton, Tiffany Green. "*Pregnancy-Related Weight Gain among Immigrant and Migrant Mothers in the United States: Do the relationships differ by Race/Ethnicity?*"

Other Working Papers

Tiffany Green, **Muloongo Simuzingili**, Peter Cunningham, Bassam Dahman. *"Impacts of the Affordable Care Act on Preconception Weight and Maternal Weight Gain: Variation by Race/Ethnicity and Nativity"*

Yaniv Hanoch, Ph.D, **Muloongo Simuzingili, MCom**, Andrew Barnes, Ph.D "*The role of optimism and pessimism bias in willingness to be treated and pay for medical services*" Journal of Risk Analysis

Brooke Albright-Trainer, Gabriel Beluchukwu, Christina Johnson, Kenneth Stutz, Rizelle Baul, Swati Pal, Bhetwal Narayan, **Muloongo Simuzingili**, Michael Kazior. "*Retrospective Comparison of Liposomal Bupivacaine Single Shot versus Continuous Catheter Interscalene Nerve Block for Post-Surgical Pain Control after Shoulder Arthroplasty."*

Peer-Reviewed Conference Presentations

- "What Influences Demand for Cigars among African American Adult Cigar Smokers? Results from a hypothetical purchase task" *SRNT Virtual Spring Meetings, 2021*
- "Racial/Ethnic Differences in Medicaid Expansion on Pregnancy-Related weight*."* Presented at *Sadie Collective Conference, 2020*
- "Income and Birth Outcomes: Examining the Mechanisms of the Earned Income Tax Credit." Presented at *Association for Public Policy Analysis and Management (APPAM) Fall Conference*, 2019
- "Pregnancy-Related Weight and Postpartum Depressive Symptoms: Do the relationships differ by race/ethnicity." Presented at the *15th Annual Women's Health Research Day*, 2019
- "The Impact of State Medicaid Expansion Waivers on Breast Cancer Screening." Presented at the *Association for Public Policy Analysis and Management (APPAM) Student Conference*, 2019
- "The Association of Provider Experience and Adherence to Colonoscopy Practice Guidelines on Polyp and Adenoma Detection Rates" Presented at *William & Mary Graduate Symposium*, 2019

Consulting

- "The Implications of Copper Price Fluctuations in Zambia" Commissioned by African Forum and Network on Debt and Development (AFRODAD), 2017. Role: Principal Investigator
- "2016 Civil Society Organization (CSO) Sustainability Index" Commissioned by USAID, 2017. Role: Principal Investigator
- "An analysis of the Implementation of the ESA (Eastern and Southern Africa) commitments on Comprehensive Sexual Education (CSE) and Sexual Reproductive Health Rights (SRHR)" Commissioned by Restless Development, 2016. Role: Principal Investigator
- "A rapid assessment of Gender Responsive Public Service Delivery in the Education and Agriculture sector". Commissioned by Action Aid Zambia, 2016. Role: Principal Investigator
- "2015 Civil Society Organization (CSO) Sustainability Index" Commissioned by USAID, 2016. Role: Principal Investigator

Invited Speaker

"How women leaders are shaping Africa and development prospects". Session Moderator at the **USA-Africa Business Expo and Networking**, Richmond VA, USA. 2019

Leadership & Volunteerism

Treasurer, **Academy Health Student Chapter**, (2019 – 2020)
Review Committee member**, 2020 APPAM Equity and Inclusion Fellowship Application**, 2020

Awards and Honors

Inaugural Research Scholar for Exemplary Work in Economics and Related Fields Research. Awarded by the Sadie Collective, 2020
Equity and Inclusion Fellowship Award in recognition of accomplishments and bright future. Awarded by the Association of Public Policy Analysis and Management, 2019
Research Scholarship. Awarded by the National Income Dynamics Study, 2012

Professional Bodies

American Association of Health Economists, 2019 – Present
Association of Public Policy Analysis and Management, 2019 – Present
Economics Association of Zambia, 2013 - 2017

Multimedia

"Post-election Challenges for Zambia", 2015. Role: Author. Blogpost for the London School of Economics: http://eprints.lse.ac.uk/81929/1/Post-election%20challenges%20for%20Zambia%20-%20IGC.pdf