A Five-Dimensional Framework for Measuring Poverty in the Context of Multifaceted Cash Transfer Programs

[THESIS]

Submitted by: Mashiat Hossain

Supervisor: Dr. Francesco Cecchi

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Contents

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Abstract

Eradicating poverty of all forms is the greatest of all global challenges and is crucial for sustainable development. Evidence from a randomized control trial found that multifaceted cash transfer programs have a long-lasting positive impact on the poor. However, there is a lack of framework available for the development organizations to monitor, evaluate, and assess whether the multifaceted cash transfer programs they implement effectively eradicate poverty across all its dimensions on which their intervention can have an impact. Therefore, this research proposes a five-dimensional framework for monitoring, evaluating, and assessing the efficiency of multifaceted cash transfer programs in addressing poverty. The five dimensions include health, living standard, income and assets, social capital, and capacity. Afterward, the research employs propensity score matching to test the framework by using secondary data collected from the beneficiaries of a multifaceted cash transfer program implemented in Rwanda. The results show a significant positive impact on all five dimensions, verifying the framework.

Keywords: Poverty eradication, Multidimensional poverty, Multifaceted cash transfer programs

Introduction

The United Nations (2020) reports that more than 700 million people in today's world live in extreme poverty, struggling to fulfill their basic needs, such as health, education, and access to water and sanitation, to name a few. According to the World Bank (2022), up to 95 million additional people could live in extreme poverty in 2022 due to Covid-19. Poverty alleviation can yield several positive social impacts, including higher nutritional and health levels, improved access to education, and employment opportunities (Cochran et al., 2019). Hence, poverty reduction and eradication have been crucial goals in international development frameworks such as the Millennium development goals [1] (2000) and Sustainable development Goals [2] (2016). Moreover, development organizations aiming to help the poor implement multiple interventions such as microfinance, unconditional, conditional, and multifaceted cash transfer programs, social safety net programs, social insurance schemes, and social assistance payments to eradicate poverty (Singh & Chudasama, 2020). Among the interventions, multifaceted cash transfer programs have gained credibility as an effective poverty alleviation tool. Multifaceted cash transfer interventions combine cash transfers with other interventions such as business training (Gobin & Santos, 2015.), capacity building (Njoroge, 2019), and personal coaching (Brune, 2020), therefore tackling multiple problems of the poor at once. Banerjee and Duflo (2015) found multifaceted cash transfer programs efficient in raising the income and consumption of poor households in multiple countries.

In addition to income and consumption, the intervention positively impacts other dimensions of human development, such as physical and mental health, food security, and assets in the countries mentioned above (Banerjee et al., 2015). Due to its proven efficiency, multifaceted

[1] The first goal of the Millennium Development goal is “eradicate extreme poverty and hunger.”

[2] The first goal of Sustainable development goals is “end Poverty in all its forms everywhere.”

cash transfer programs are now widely used by development organizations such as Save the Children (2017), UNICEF (2021), and Food and Agriculture Organization(2021) as a tool for poverty eradication. However, there is a lack of framework, accounting for all the dimensions mentioned above, which the development organizations can use to assess if their respective multifaceted cash transfer interventions successfully address poverty. Formulating such an intervention-specific poverty measurement framework will contribute to the effective monitoring, evaluation, and impact assessment of multifaceted cash transfer programs implemented by the development organizations.

Therefore, in Chapter 1 of this paper, I first give an overview of the definitions and available methods of measuring poverty. Then, in Chapter 2, I further discuss the missing elements in existing methods of measuring poverty and propose a five-dimensional framework to assess poverty in the context of multifaceted cash transfer programs.

In Chapters 3 and 4, I test my framework using secondary data gathered from the beneficiaries of a multifaceted cash transfer program implemented in Rwanda. As mentioned previously, Banerjee and Duflo (2015) have conducted a randomized control trial in Ethiopia, Ghana, Honduras, India, Pakistan, and Peru to test the effect of multifaceted cash transfer programs on most indicators I use in my framework (Banerjee, 2015). Yet, evaluating the framework using the data in Rwanda will broaden the understanding of whether a multifaceted cash transfer program is an effective tool to address poverty in the context of Rwanda.

Moreover, the data utilized to test the framework is collected between June 2020 to January 2022. In March 2020, the World Health Organization (2020) declared a global pandemic due to the outbreak of Covid-19. The World Bank (2021) reported that poverty in Rwanda has been dramatically increasing in rural and urban areas due to Covid-19. Moreover, the poverty headcount ratio in the country is likely to rise by 550,000 people in 2021, compared to a no-covid scenario (World Bank, 2021). Therefore, as this research utilizes a dataset collected during Covid-19, it will also contribute to a better understanding of the effectiveness of multifaceted cash transfer programs in addressing poverty during a global pandemic like Covid-19.

Chapter 1-Overview of Defining and Measuring Poverty

1.1 What is Poverty?

Traditionally, poverty is conceptualized as income deficiency leading to a lack of wellbeing for the poor, which makes us question: What does this lack of income result in which makes people poor? According to the absolute poverty approach, the lack of income in question results in failure to fulfill one's essential physiological needs (Bowley & Rowntree, 1941). On the other hand, according to relative poverty, the lack of income results in failure to meet the average standard of living in the country where one lives (Foster, 1998). In both cases, lack of income is used as a proxy for wellbeing.

However, assessing poverty solely based on income started being criticized because it neglected other dimensions that poverty can affect (Whelan, 2004). Chambers (2012) argues that the reality of the poor is much more dynamic and complex; it is not only having a lack of income. For instance, a person with a parasitic infection might need more nutrition- hence more income to sustain him/herself than a person who does not have a parasitic infection (Fusco, 2003). In such a case, using only an income threshold as a proxy for everyone's wellbeing is not ideal for defining poverty (Fusco, 2003). Further, the unidimensional concept of poverty implies that having adequate income ensures wellbeing for everybody. Such a "one size fits all" approach to assessing wellbeing denies the opportunity to choose what wellbeing might mean at an individual level (Fusco, 2003). Fusco (2003) further argues that "the freedom of the individual to choose is a fundamental constituent of wellbeing. So, being deprived of it constitutes a clear reduction in wellbeing." Therefore, during the 1970s, poverty started getting recognition as a multidimensional phenomenon, as the unidimensional approach to conceptualizing poverty failed to take into account the complex and diverse situations of the poor.

To come up with a better understanding of poverty, the criticism of using income as a proxy for wellbeing called for a need to rethink the concept of wellbeing itself. Amartya Sen (1985) asserts that just because a person might have adequate income does not mean income will automatically translate into wellbeing. It is needed to assess whether an individual is capable of translating his/her income or any other material commodities into his/her respective wants. Hence, dimensions such as individual circumstances and environment should be considered while measuring poverty (Sen, 1985). Before Sen, multiple other scholars coined factors such as lack of rights, social exclusion, and lack of basic security while conceptualizing poverty (Spicker, 2010).

By the 1990s, the idea of poverty as a multidimensional phenomenon had become widely recognized. In 2000, the World Bank performed a qualitative research 'Voices of the Poor' where opinions of more than 60,000 poor women and men from 60 countries were collected to understand poverty from their perspectives. In the research, several themes such as problems of physical health, lack of security, and social exclusion recurred alongside lack of income which expanded the understanding of poverty and its complex realities (Narayan-Parker, 2000).

At the beginning of 2000, poverty gained popularity as a social concept. Recognizing the complex and diverse situation of being poor, the European Union started using social exclusion as a proxy for poverty (Aasland & Fløtten,2001). However, Aasland & Fløtten (2001) argue that although poverty and social exclusion have overlapping factors, they are not identical. Lister (2016) explains; that poverty is not only a material disadvantage and economic insecurity but is also a 'shameful and corrosive social relation,' characterized by a lack of voice, disrespect, humiliation, and reduced dignity and self-esteem. Thus, the pedagogy of poverty faced a radical departure from previous historical approaches to defining poverty unidimensionally.

Although poverty has received significant attention in academia during the last couple of decades, the debate regarding how to define poverty is still going on. As Paul Spicer says, “Poverty does not have a single meaning. It has meanings linked through a series of resemblances (Spicker, 2010).” Further, Fusco (2003) asserts “that each different existing definition and measure takes into account a peculiar facet of poverty. Each definition contains a part of the truth, but no single definition holds the truth in defining poverty.”

1.2 Measuring Poverty

As the definition of poverty evolved, the ways to measure it have also evolved alongside it. During the 1960s, poverty was measured by an income benchmark developed by comparing pre-tax income against a threshold set at three times the cost of a minimum food diet adjusted for family size (Fisher, 1992). The World Bank later created a new way of measuring poverty based on the basket of goods approach. The basket of goods refers to the goods necessary for a household to maintain a basic living standard according to the context they live in (Foster, 1998). In 2005, the World Bank estimated the minimum requirement to attain all the necessary goods to be 1.25 dollars per day, which was later changed to 1.90 dollars in 2011(Ferreira et al., 2016). While the former measurement, which only took minimum food diet into account, is based on the concept of absolute poverty, the later measurement based on the "basket of goods" was derived from the concept of relative poverty (Foster, 1998). Nevertheless, both of the measurements only took income into account.

The need to formulate a broader measure of poverty rather than only income emerged as the understanding of poverty evolved from being unidimensional to a multidimensional phenomenon.

In 1966, United Nations Research Institute for Social Development conducted 20-country research and formulated a "level of living index," which comprised of three categories such as physical needs (nutrition, shelter, and health); cultural needs (education, leisure, and security); and higher needs (measured as income above a threshold) (Drewnowski & Scott, 1966). Later in 1972, UNRISD conducted a second study and released a "development index" consisting of 9 economic and 9 social indices (McGranahan et al., 1972). In 1976, the International Labour Organization (ILO) started measuring welfare with basic needs approach. ILO identified basic needs as access to clothing, housing, education, and transport (Ghai & International Labour Office, 1977). Later, employment and participation in decision-making were also included in the index. It should be pointed out that the indicators included in measuring basic needs have varied over time (Emmerij, 1984).

In 1979, the Overseas Development Council released the Physical Quality of Life Index (PQLI). It included infant mortality, life expectancy at the age of one year, and basic literacy to assess whether the poorest people meet a minimum number of basic needs (Estes, 2014). Later, in 1989, the "International Human Suffering Index," comprising ten indices, including income, infant mortality, nutrition, adult literacy, and personal freedom, was developed(Kelley, 1989).

In 1995, based on Amartya Sen's capabilities approach to defining poverty, the United Nations Development Programme released the Human Development Index. It focused on three essential components: a long and healthy life, knowledge, and access to resources needed for a decent standard of living to measure the development of a country at a macro level

(UNDP,1995). In 2010, UNDP used the same indices and released the Multidimensional Poverty Index to measure deprivation of wellbeing at the household level. The multidimensional poverty index suggests three dimensions for assessing poverty: education, health, and standard of living. In the dimension of education, years of schooling and child enrolment are measured; for the dimension of health, child mortality and nutrition are measured; and for the standard of living, electricity, drinking water, sanitation, flooring, cooking fuel, and assets are measured (Kovacevic & M Cecilia Calderon, 2016).

Table 1: Existing Tools for Poverty Measurement

Name of Measurement Methods	**Used Indices**
Poverty Benchmark	Income
Basket of Goods Approach	Income
Level of Living	Nutrition, Shelter, Health, Education, Leisure, and Security measured as income above a threshold
Development Index	The expectation of life at birth 2. Population in localities, Consumption of animal protein, per capita, per day, Combined primary and secondary enrollment as a percent of age group 5-19, Vocational enrollment as a percent of age group 15-19, Average number of persons per room, Newspaper ('daily general interest') circulation per 1000 population, Telephones per 100,000 population, Radio receivers per 1000 population, percent of the economically active population in electricity, gas, water, sanitary services, transport, storage, and communications, Agricultural production per male agricultural worker, in 1960 U.S. dollars, Adult male labor in agriculture as a percent of total male labor (, Electricity consumption, kwh. per capita, Steel consumption, kg. per capita 15. Energy consumption, kg. of coal equivalent per capita 16. GDP derived from manufacturing as a percent of total GDP, Foreign trade (sum of imports and exports) per capita, in 1960 U.S. dollars, Salaried and wage-earners as a percent of the total economically active population, GNP
Basic Needs Approach	Clothing, housing, education and transport, employment, participation in decision making
Physical Quality of Life Index (PQLI).	The basic literacy rate, rate of infant mortality, and average years of life expectancy at age one

International Human Suffering Index	Life expectancy, daily calorie intake, clean drinking water, infant immunization, secondary school enrolment, GDP per capita, rate of inflation, communications technology, political freedom, and civil rights
Human Development Index	Life expectancy at birth, expected years of schooling, mean years of schooling, GNI per capita
Multidimensional Poverty Index	Electricity, drinking water, sanitation, flooring, cooking fuel assets, years of schooling, child enrolment, child mortality, and nutrition

Chapter 2: Theoretical Framework

This Chapter discusses the missing dimensions of the available tools to measure multidimensional poverty and further proposes a five-dimensional framework for measuring poverty in the context of multifaceted cash transfer programs.

2.1 Missing Dimensions in Measuring Multidimensional Poverty

The existing methods of measuring multidimensional poverty have met with criticisms for not considering environmental, social, political, and psychological aspects of wellbeing (Strotmann & Volkert, 2018; Navarro, 2001; Alkire, 2007). Despite being aware of a wide range of possible dimensions that could be included in measuring poverty, this section will only discuss dimensions of psychology, social capital, and capacity. As multifaceted cash transfer programs directly impact the three dimensions mentioned above (elaborated in section 2.2), they are relevant to this research.

Psychological Dimension

Multiple multidimensional poverty measurement methods take the dimension of health into account. However, they only focus on physical health-related indices, neglecting the psychological aspect of poverty. Recent studies have revealed that poverty induces specific behaviour among the poor such as risk averseness and short-sightedness, which in turn causes people to act in ways that further trap them into poverty (Haushofer & Fehr, 2014). Such a finding shows the importance of considering psychological wellbeing while measuring poverty.

Social capital

Considerable empirical research has shown a negative association between poverty and negative social consequences, such as harmful effects on relationships with friends and relatives (Mood & Jonsson, 2016; Hjalmarsson & Mood, 2015). The poor rely heavily on their social network to cope with various effects of poverty (Afridi, 2011). A lack of reliable social networks can act as a mechanism that can further induce poverty (Matthews & Besemer, 2015), which makes it necessary to include social capital as one of the dimensions while assessing multidimensional poverty.

Capacities

Sen's (1985) capacities approach explains focusing on individual capacities to attain his/her desired outcome is more important than measuring the outcome itself. However, most poverty measurement indexes such as the Human Development Index and Multidimensional Poverty Index still focus on output such as access to income, electricity, cooking fuel, and education rather than the capacity of an individual to access them. Such an outcome-oriented poverty measurement approach could limit the understanding or even give a false impression of poverty reduction. The experience of poverty differs from person to person based on their unique situation. Hence, different individuals might need to achieve different outcomes and, in fact, different levels of outcome given their respective conditions. Let us consider the example described in section 1.1 by Fusco (2013); a person having a parasitic infection might have different nutritional needs compared to a person who does not have a parasitic infection. In such a context, using a poverty measurement tool that only accounts for the outcome of nutrition can show that both individuals with and without parasitic infection have equally improved in the outcome of nutrition. Nevertheless, the factor of whether the person who needs more nutrition due to his/her specific health condition has the capability to attain more nutrition if needed will remain unexplored. Therefore, measuring the capacity of the poor to achieve their desired needs suited to their individual situations will give us a better understanding of poverty eradication at an individual level compared to only measuring attainments of specific outputs such as nutrition. Thus, while rethinking the dimensions of poverty, human capacities must receive thorough attention in newer measurement methods of multidimensional poverty.

2.2 Cash Transfer Programs and their Impacts

Even if there is a lack of agreement regarding the definition of poverty and ways to measure the phenomenon, it is widely agreed that poverty should be eradicated. Hence, the subject of poverty reduction and eradication has occupied significant space in development policy and program implementations. In such a scenario, cash transfer interventions have received much interest in academia as it is considered to be an efficient tool to tackle poverty (Hagen-Zanker & Leon Himmelstine, 2016).

A cash transfer program (CTP) refers to all programs where cash (or vouchers for goods or services) is directly provided to the beneficiaries. There are three types of cash transfer programs, conditional cash transfer programs, unconditional cash transfer programs, and multifaceted cash transfer programs. The following paragraph will briefly overview different cash transfer programs and review their impact from existing literature. Further, based on the factors on which cash transfer programs have a direct effect, this research will formulate a framework that can be used to measure multidimensional poverty in the context of multifaceted cash transfer programs.

Conditional cash transfer programs: Conditional cash transfer (CCT) programs aim to reduce poverty by making welfare programs conditional upon the receivers' actions.

Conditional cash transfer programs have positively impacted consumption (Asfaw et al., 2014) and living conditions (Handa et al., 2018; Gertler et al., 2012). Further, factors such as school attendance of children (de Brauw & Hoddinott, 2011; Millán et al., 2019), productive assets (Asfaw et al., 2014; Bastagli et al., 2019; Rigolini, 2016), social capital (Attanasio et al., 2015), and entrepreneurship skills (Ribas, 2020) are also positively impacted by conditional cash transfer programs. However, conditional cash transfer programs have mixed effects (positive or negative) on beneficiaries' psychological health (Ohrnberger et al., 2020; Ohrnberger et al., 2020).

Unconditional cash transfer program: Under unconditional cash transfer programs, beneficiaries do not have to adhere to any conditions for receiving cash. Unconditional cash transfer programs positively impact household income (Sabates et al., 2019), investment (Handa et al., 2018), and productive assets (Haushofer & Shapiro, 2016). The intervention has also proven to be effective in improving psychological health (Haushofer & Shapiro, 2016), decreasing morbidity and food insecurity (Novignon et al., 2022), and school attendance (Sabates et al., 2019).

Multifaceted cash transfer programs: The limited impact of "one constraint at a time" approach, such as providing only cash through unconditional cash transfer programs, or targeting one policy through conditional cash transfer programs in reducing poverty has demanded the need to rethink interventions that can simultaneously address multiple constraints of the poor (Gobin and Santos, 2015). Multifaceted cash transfer programs are gaining popularity in combatting poverty as it combines several other interventions such as business skills training (Gobin and Santos, 2015), capacity building (Njoroge, 2019), and personal coaching (Brune et al., 2020) along with cash transfers.

From a randomized control trial among six countries, Abhijeet Banerjee and Esther Duflo (2015) found that multifaceted cash transfer programs positively impacted 9 indicators. The indicators include consumption, food security, financial inclusion, assets, time spent to work, income and revenue, physical health, mental health, political inclusion, and women empowerment.

It must be mentioned; within my review of literature, I found the prior-mentioned research to be the only one that conducts such a robust study regarding the impact of multifaceted cash transfer interventions on 9 indicators, which makes this research the second one to do so within my knowledge.

2.3 Poverty measurement in the Context of Multifaceted Cash Transfer Programs

Multifaceted cash transfer programs have proven to have a long-lasting positive impact on the poor (Banergee & Duflo, 2015). Due to its potential to address multiple deprivations of the poor at once, development organizations widely implement multifaceted cash transfer programs to combat poverty (Save the Children, 2017; UNICEF, 2021, FAO, 2021). Such popularity of multifaceted cash transfer programs surfaces the need for an intervention-specific sophisticated framework to assess whether the implemented interventions are successful in poverty eradication or reduction. Therefore, in the next segment of this section, I review the aspects on which multifaceted cash transfers could impact the poor based on existing literature. Further, based on that review, I propose a framework that can be utilized to measure poverty in the context of a multifaceted cash transfer program.

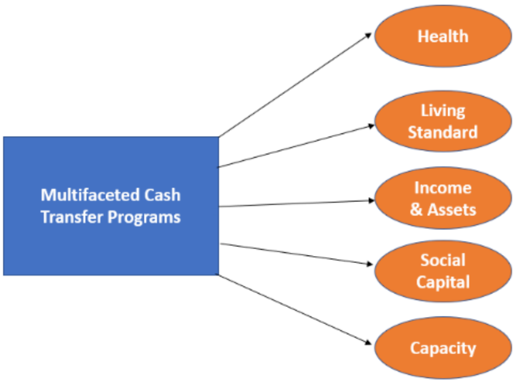
As critiques of conditional and unconditional cash transfers are considered in multifaceted cash transfer programs (Gobin and Santos, 2015), I assume that the impact found for conditional and unconditional cash transfers will also retain in multifaceted cash transfer programs. Therefore I propose the framework based on factors on which not only multifaceted cash transfer programs have an impact, but also conditional and unconditional cash transfer programs exert impact. Later on, I test this assumption using data obtained from the beneficiaries of a multifaceted cash transfer program. Based on the recurring factors from the literature review, I propose five dimensions be taken into account while measuring multidimensional poverty in multifaceted cash transfer programs.

Table 2: Dimensions Impacted by a Multifaceted Cash Transfer Program

Dimensions	Outcomes from impact measurement
Health	Improvement in *physical health* (Robertson et al., 2013; Ranganathan & Lagarde, 2012; Attanasio, 2006) and mixed effect on *psychological health* (Ohrnberger et al., 2020; Ohrnberger et al., 2020)
Living Standard	Improved *living standards* (Handa et al., 2018); Gertler et al., 2012).
Income and Assets	Increased *productive assets* (Haushofer & Shapiro, 2018; Asfaw et al, 2014; Bastagli et al., 2019; Rigolini, 2016) and *income* (Haushofer & Shapiro, 2016; Banerjee et al., 2015)
Social Capital	Increased *political participation* (Schober, 2019; Banerjee et al., 2015) and Improved *social relationships* (Attanasio et al., 2015; Attanasio et al., 2009)
Capacity	Increased *school attendance* (de Brauw & Hoddinott, 2011; Millán et al., 2019), and entrepreneurship skills (Ribas, 2020)

As shown in Table 2, multifaceted cash transfer programs can address deprivation in multiple aspects of multidimensional poverty, which can be divided into five dimensions: health, living standard, income and assets, social capital, and capacity.

Figure 1: Dimensions of Poverty Impacted byMultifaceted Cash Transfers



However, as discussed in Section 2.2, the existing measurements of poverty fail to include all the dimensions mentioned in Table 2. Given such a circumstance, using existing poverty measurement tools to assess the success of a multifaceted cash transfer program in addressing poverty would provide a narrower understanding of the efficiency of the said intervention in poverty reduction or eradication.

Therefore, I propose monitoring, evaluation, and impact assessment of measuring multidimensional poverty in the context of a multifaceted cash transfer program should rely on a framework that includes the dimensions of health, living standard, income and assets, social capital, and capacity. It is crucial to note that the framework only indicates the dimensions which should be included while measuring poverty in contexts where multifaceted cash transfer programs are implemented. It does not point towards a cutoff that would indicate the success of such interventions, as the robustness of the impact of a multifaceted cash transfer program can vary based on the type of interventions combined with cash transfers and also on how long the said intervention would last[3].

[3] A multifaceted cash transfer program that lasts provides cash to beneficiaries for one year should have different impact than a multifaceted cash transfer program that provides cash to beneficiaries for two years. Also, a multifaceted cash transfer program that provides training on entrepreneurship is supposed to have lessrobust outcome compared to a multifaceted cash transfer program that provides training on nutrition or hygiene.

In the following Chapters of this paper, I test my prior-mentioned framework of measuring poverty in the context of multifaceted cash transfer programs by assessing whether a multifaceted cash transfer program impacts the five dimensions proposed in the framework.

Chapter 3: Testing the Framework

Chapter 3 of this paper will discuss the procedure of assessing the impact of multifaceted cash transfers on four dimensions of the proposed five-dimensional framework: health, living standard, capacity, and social capital. The dimension of income and assets should include information regarding both income and assets. However, due to insufficient data available regarding the beneficiaries' income, Chapter 3 will only discuss the impact of multifaceted cash transfer interventions on assets. Lists of questions used to construct the dimensions and the subdimension are attached in Annex A. Chapter 3 will contain sections describing the data source and sampling, hypotheses, methodology, and results of the procedure. I will elaborate on the impact of multifaceted cash transfer programs on income in Chapter 4.

3.1 Poverty in Rwanda

As the research will utilize data collected from the inhabitants of rural Rwanda, I find it essential to give a brief overview of the poverty status and implementation of multifaceted cash transfer programs in Rwanda before diving into methodological details. Two decades ago, shuttered by a genocide, Rwanda, a landlocked state in Sub-Saharan Africa, was considered one of the world's poorest countries (Uvin, 1998). However, as measured by the national poverty line, poverty declined from 77% in 2001 to 55% in 2017 (World Bank, 2022). Moreover, according to the World Bank (2022), life expectancy at birth improved from 29 in the mid-1990s to 69 in 2019. With the emergence of the pandemic; Covid-19, poverty reduction is projected to decelerate from 43 percent in 2019 to 41.9 percent in 2020-2021 (World Bank, 2020).

Nevertheless, the macro-level statistical analysis conducted to generate the prior-mentioned numbers are widely criticized for not accounting in-depth realities of the living conditions in rural Rwanda (Ansoms et al., 2017). Although the numbers report promising outcomes in terms of meeting the national socio-economic targets of poverty reduction, research focusing on access to productive assets such as land and property, individual freedom, and the ability to participate in decision-making procedures in Rwanda portrays a contrasting picture regarding multidimensional poverty reduction in the country (Dawson, 2015). In addition, the World Bank (2021) reports that Rwanda's economy has fallen into its first recession due to Covid-19, which can leave a lasting impact on the economy. Given such context, multiple development organizations[4] have been implementing multifaceted cash transfer programs to address poverty in Rwanda, raising the need for a framework to assess the efficiency of such interventions in poverty reduction/eradication.

3.2 Data Source and Sampling

100WEEKS is an NGO that offers weekly training sessions, access to a savings association, and a cash transfer of 8 euros/week for 100 weeks to women in Rwanda, Uganda, Ghana, and the Ivory Coast to uplift their beneficiaries from poverty. For this research, I will utilize secondary data collected to monitor and evaluate 100WEEKs intervention in Rwanda[5] to test my proposed framework. The undergraduate students of a university named Ines-Ruhengeri, who work as enumerators for the 100WEEKs team in Rwanda, collect the data from the beneficiaries of 100WEEKs. Afterward, 100WEEK's monitoring and evaluation team stores

[4]Concern Worldwide (2021); Imarisha, and Score (USAID, 2019)

[5] I choose Rwanda as 100WEEKs is active in Rwanda over the longest period of time compared to the other countries and therefore can provide us with. It was the only location from which I could generate a sample size of 722 beneficiaries which was used to test our frameworks. The other locations did not have enough data to perform such an analysis.

the data in a dashboard called 100WEEKs central. The survey comprises 65 components containing indicators that can capture my dimensions of interest.

In Rwanda, 100WEEKs works closely with a local partner, Caritas, and local priests to implement their intervention. 100WEEKs takes the following steps to choose the location and the beneficiaries, which is also the sampling procedure of my data:

a. **Village selection**: The local partner of 100WEEKs, Caritas conducts the first step of selecting villages for the 100WEEKs program.
b. **Contacting the local priest**: Afterwards, Caritas reaches out to the local priest of the corresponding village as the first point of local contact.
c. **Coach selection**: When the priest agrees to cooperate with the 100WEEKS team, the Caritas team asks the priest to select several "coaches" out of the community. 100WEEKs then employs the coaches to provide training to the potential beneficiaries of 100WEEKs.
d. **Beneficiaries selection**: The final step of the selection process is selecting the beneficiaries to participate in the 100WEEKs program. The beneficiaries are selected combinedly by the 100WEEKs team, the local priests, and coaches following the below-mentioned criteria:
    1) Being a woman
    2) Being poor[6]
    3) Owning a small business to prove her desire and motivation to move out of poverty
    4) Aged between 20-40
    5) Not enrolled in any other intervention at the moment of participation in the 100WEEKs program

[6] 100WEEKs interview the beneficiaries regarding their economic status, occupation, number of household member who earns an income to determine whether they are poor. No fixed criteria or cutoff exist for determining the poverty status of the beneficiaries.

As I utilize secondary data in this research, I constructed the five dimensions based on the available data. Later, I formulated the hypotheses regarding the five dimensions based on the indexes and variables included in each dimension.

3.3 Constructing the Dimensions and Subdimensions

After obtaining the data from the 100WEEKs team, I used 49 out of 65 indicators from the survey to construct the dimensions of health, living standard, social capital, capacities, and the subdimension of assets following the below-mentioned procedure:

Health

Health is a state of complete physical, mental and social wellbeing and not merely the absence of disease or infirmity (World Health Organization, 1946). Based on the available data, I constructed the dimension of health using two subdimensions: psychological health and nutrition. Increasing evidence suggests that psychological health is related to lower disease and mortality risk (Trudel-Fitzgerald et al., 2019). Therefore psychological health is an essential component of overall health. Additionally, proper nutrition is associated with positive physical health outcomes (Ohlhorst et al., 2013), making nutrition a vital element of health. Therefore, I constructed the two sub-dimensions of psychological health and nutrition as follows:

Psychological Health: I used the general health questionnaire (GHQ), comprised of 12 questions, to measure the dimension of psychological health. The general health questionnaire is a psychometric screening tool to identify common psychiatric conditions (Montazeri et al.,

[7] Exploratory factor analysis is a multivariate technique that is used to identify the smallest number of factors/dimensions that can explain the covariation observed among a set of measured variables (Watkins, 2018). Principles components analysis is another similar method that is used to find out the smallest number of dimensions that can explain the variation in the data. Unlike principles component analysis, exploratory factor analysis assumes that there is a latent variable that is influencing the results of the factors/dimensions(Watkins, 2018. In our research, I assume, that the answers of the general health questionnaire is influenced by the latent variable of health, therefore I use exploratory factor analysis.

2003). I conducted an exploratory factor analysis[7] among the 12 questions of the GHQ, which generated one factor with an eigenvalue above 1. Further, I predicted a factor score named "psychological_health" for each observation in the sample to represent the psychiatric conditions of the participants. Additionally, after conducting the factor analysis, I checked the internal consistency within the variables using the Kaiser Meyer Olkin test (KMO). The result was above 0.6, indicating an acceptable level (See ANNEX B table 1).

Nutrition: I used food quantity and quality as a proxy of nutrition as per the guideline for calculating the dietary diversity index[8] provided by Food and Nutrition Technical Assistance (Swindale and Bilinsky, 2006). I constructed one variable named "nutrition" by summing up the number of unique food groups consumed in the household of each participant in the sample during the last seven days. In the summation procedure, consuming each type of food received a value of 1, and not consuming them received a value of 0. Food groups that were considered were 1. Meat (This includes any type of meat, including chicken or other poultry) 2. Fish (Any fresh or dried fish or shellfish. 3. Milk or milk products (This includes any dairy products, such as cheese or butter) 4. Eggs (this includes any meal prepared with eggs) 5. Plantains or Root Vegetables (Such as Cassava, Potatoes, Yams, or Plantains) 6. Beans 7. Other vegetables (This includes all types of vegetables that do not fall under the last category. For example, mushrooms, cabbage, Dodo, spinach, Inyabutongo[9]) 8. Any fresh fruit. 100WEEKs extracted the list from the survey used for calculating the dietary diversity index by FANTA (Swindale and Bilinsky, 2006). Further, they adapted the list to local standards based on the input of local employees of 100WEEKs.

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[8] Dietary diversity is a qualitative measure of food consumption that reflects household access to a variety of foods and is also a proxy for nutrient adequacy of the diet of individuals (Swindale and Bilinsky, 2006).

[9] A green vegetable

I must mention that the generated dietary diversity score does not capture the nutritional status of the entire household, as data regarding children below five years of age was unavailable. Further, the guideline for calculating the dietary diversity index by Food and Nutrition Technical Assistance (Swindale and Bilinsky, 2006) recommends capturing the number of diverse food intakes in the last 24 hours. However, the survey question used for calculating the dietary diversity index for this research only allowed to capture different types of food consumed in the last seven days, resulting in a less precise proxy of nutrient adequacy for each household (Swindale and Bilinsky, 2006).

Finally, to construct the dimension of health, I generated a variable named "health" using the following formula:

(1) Health= z_(z_nutrition + z_psychological_health)

In the formula, z_nutrition is the standardized version of the variable "nutrition"; similarly, z_psychological_health is the standardized version of the variable "psychological_health." I standardized the subdimensions to allow the summation of vastly different concepts such as psychological health and nutrition and to further ensure that both subdimensions are given equal weight while constructing the dimension of health.

It is crucial to mention that the poor often face meager water, sanitation, and hygiene conditions, making them vulnerable to certain diseases such as parasitic infections, malaria, typhoid, and diarrhea (Bornstein, 2018). That being the case, it is necessary to capture data regarding morbidity, while constructing the dimension of health. Morbidity reflects whether the respondent have been sick in the recent past. Despite having questions regarding morbidity in the monitoring and evaluation survey of 100WEEKs, I could not include the aspect of morbidity in the dimension of health due to insufficient observations available for the question (elaborated in detail in Chapter 5). However, I strongly recommend that data regarding morbidity should be included while constructing the dimension of health in future research.

Living Standard

No particular definition of living standard is agreed upon in social science (Cottam & Mangus, 1942). While some scholars define it as consuming material goods, others emphasize satisfaction (Cottam & Mangus, 1942). Within this research, I constructed the dimension of living standard with two sub-dimensions; material wellbeing and food security. Existing research has confirmed the need for basic materials to maintain a decent living standard (Rao & Min, 2018). Further, according to the International Covenant on Economic, Social, and Cultural Rights (ICESCR)[10], adequate food is a vital element of living standard (OHCHR, 1996). Therefore, in addition to material wellbeing, HFIAS, an externally validated index to measure food insecurity, was included in the dimension of living standards (Coates, Swindale, and Bilinsky, 2007). Hence, I formulated the sub-dimensions mentioned above as follows:

Material Wellbeing: I used the indicators suggested in the "living standard" section of the Multidimensional Poverty Index (MPI) to construct the sub-dimension of material wellbeing. The indicators include access to electricity, clean drinking water, sanitation, flooring, cooking fuel, and assets (Alkire and Santos, 2011). I must point out that although I used the indicators suggested in the MPI; I did not follow the methodology proposed in the MPI. It is because the proposed method in MPI only captures the binary outcome of whether the household is deprived/not deprived of the essential materials required for standard living. Thus, it fails to show any improvement or deterioration caused by the multifaceted cash transfer program. For example, there could be households that, despite having made significant improvements in

[10] **Article 11.1** states that: "The States Parties to the present Covenant recognize the right of everyone to an adequate standard of living for himself and his family, including adequate food, clothing and housing, and to the continuous improvement of living conditions (OHCHR, 1996)."

owning the essential materials, might still not make it to the requirement of being “not deprived” according to the standard of the multidimensional poverty index. This research aims to test the proposed framework by assessing if a multifaceted cash transfer program affects the subdimension of material wellbeing. Therefore it is necessary to capture any improvements or deteriorations in the subdimension of material wellbeing rather than binary outcomes. Furthermore, a multifaceted cash transfer program can have various compositions of interventions that might impact the subdimension of wellbeing in multiple ways. Following such reasoning, whether a multifaceted cash transfer program can reduce the deprivation of material wellbeing based on the criteria suggested by the MPI depends on the combination of interventions offered by the multifaceted cash transfer programs, which are not relevant to this research.

Therefore, I constructed the subdimension of material wellbeing following the below-mentioned procedure.

a. **Electricity**: I used the lighting source as a proxy for electricity due to insufficient data regarding access to electricity. I generated a dummy variable called ‘lighting.’ It was assigned to be 1 if the reported source of electricity was the national electricity grid [REG / ECG], biogas, generator, or other electricity distributors, and 0 if it was reported to be oil lamp, firewood, candle, lantern.
b. **Clean drinking water:** Further, to capture the accessibility to clean drinking water, another dummy variable called ‘water’ was created, which was assigned to be 1 if the reported water source was a tube well or borehole, dug well (protected), water from a spring (protected) and 0, if the reported water source was water from spring (unprotected), rainwater, surface water such as water from river/dam/lake/pond/stream/canal/irrigation channel, piped into dwelling, piped to yard/plot, public tap/standpipe, dug well (unprotected). Moreover, to obtain one score that would capture the accessibility to clean

drinking water within the sample, I generated a variable named ‘drinkingwater’ by standardizing the dummy variable, ‘water’, and adding to the standardized variable of ‘timewatersource_1.’ The variable ‘timewatersource_1’ captured the time taken to access water sources in minutes. The final score for constructing the variable reflecting access to clean drinking water is as follows:

(2) drinkingwater= z_(z_water+z_timewatersource_1)

c. **Sanitation**: To capture the aspect of sanitation, I generated a dummy variable ‘toiletdummy’ which was assigned to be 1 if the reported toilet facility was a flush toilet, pit toilet, improved pit toilet, or latrine, and 0 if the toilet facility was reported to be no facility, bush, field, neighbor’s toilet, open/unimproved pit toilet without a concrete slab. Further, to obtain one score which would capture the situation of the sanitation within the sample, I constructed a variable named ‘sanitation’ by standardizing the variable; ‘toilet’ and adding to the standardized variable of ‘toiletshare.’ The variable ‘toiletshare’ captures the number of people with whom the toilet facility was shared. The equation for constructing the variable sanitation is as follows:

(3) sanitation= z_(z_toilet+z_toiletshare)

d. **Material of the floor**: I created a dummy variable called ‘materialfloordummy’ where the dummy variable was assigned to be 1 if the material of the floor was reported to be cement, bricks, wooden floor, or other solid/durable material and 0 if it was reported to be beaten earth/dung hardened, clay tiles, or other simple floors (mud/clay/sand or similar), to capture the material of the floor in the household.

e. **Cooking Fuel**: To construct the indicator for cooking fuel, I generated a dummy variable “fuel dummy” which was assigned to be 1 if cooking fuel was reported to be gas, biogas, solar power, electricity, oil/kerosene, and 0 if it was reported to be crop waste, animal dung firewood, or charcoal.

f. **Assets:** Lastly, for the indicator of assets, I used factor analysis to capture ownership of assets that are essential to living a decent life using the following questions:

1. Does any member of the household currently own a Radio / Table / Chair / Lantern or Paraffin lamp / Metal cooking pots?
2. How many beds does the household own? (a mat or mattress on the floor is not considered a bed)
3. How many mosquito nets does the household have that can be used while sleeping?
4. Do all household members own at least one pair of shoes? (this includes any kind of footwear such as slippers)
5. Do all household members own at least two sets of clothes?

I further performed Kaiser Meyer Olkin test (KMO) to check the internal consistency within the variables. The result was above 0.6, indicating an acceptable level (See ANNEX B table 2).

I must mention that according to the standard of MPI, if a household does not own more than one radio, TV, telephone, bike, motorbike, or refrigerator and does not own a car or tractor, then the household is considered deprived (Alkire & Santos, 2011). However, in my entire sample of 722 individuals who belonged to separate households, less than eight people owned a refrigerator, television, radio, or telephone, indicating a meager living standard within the sample. Hence to align with the goal to capture improvements in material well-being, I included materials needed to meet basic needs of daily life such as clothing items, utensils, and furniture, as assets in the section of material wellbeing (Rao & Min, 2018). Furthermore, as bicycles and motorcycles are considered productive assets in rural Africa (Wodon, 2007), I placed them in the subdimension of assets dedicated to capturing productive assets.

To finally generate the total score of the material well-being, I constructed a variable named 'materialwellbeing' by standardizing the summation of the standardized forms of the variables, which captured access to electricity, drinking water, sanitation, durable flooring, cooking fuel, and assets using the following equation:

(5) materialwellbeing= z_(z_lighting + z_sanitation + z_drinkingwater + z_fueldummy + z_materialfloordummy + z_assets_materialwellbeing)

Food security: I adapted the methodology of constructing the food security score from the guideline provided by the Household Food Insecurity Access Scale (HFIAS) (Coates, Swindale, and Bilinsky, 2007). While the subdimension of nutrition added in the dimension of health reflected different types of food consumed by the respondents, the food security score derived using HFIAS reflected the household's accessibility to food (Coates, Swindale, and Bilinsky, 2007).

HFIAS originally consists of 9 "occurrence" questions and 9 "frequency of occurrence questions" (Coates, Swindale, and Bilinsky, 2007). The answer options to the aforementioned 18 questions are scaled between 0 to 3. The procedure to calculate HFIAS is to sum up all the scores of the 18 questions for each household to generate a food insecurity score for each household. The lowest score of HFIAS can be 0, indicating the lowest food insecurity, and the highest can be 27 showing the highest food insecurity. Due to the lack of data, I could only use the 9 "occurrence" questions in this research. The survey structure used for data collection captured binary answers for the "occurrence" questions with 0= No and 1=Yes. Therefore, after summing up the nine questions, the results could reflect 0 as the lowest food insecurity and 9 as the highest food insecurity. Lastly, the score for food insecurity was multiplied by -1to reflect food security. The following equation can explain the procedure:

(6a) foodinsecurity={∑("occurrence" variables)}

(6b) foodsecurity= -1*foodinsecurity

Finally, to generate the score of living standard, I standardized the food security score and added it to the standardized score for material wellbeing. The summation of the two subdimensions was re-standardized to generate the final score of living standards. I used the following formula to construct the dimension:

(7) Living_standard= z_(z_materialwellbeing+z_foodsecurity)

Capacity

Capacity is the "power to do something" (Bebbington et al., 2006). In this research, I formulated the dimension of capacity with the subdimensions of agency and financial buffer. Agency focuses on the power to make decisions, and financial buffer focuses on the power to financially cope in adverse situations.

Agency: Following Sen's (1985) capability approach, only providing means to eradicate poverty is insufficient; it is needed to assess whether the beneficiaries can translate those means to climb out of poverty. Most cash transfer programs target women as beneficiaries (Bonilla et al., 2017). However, existing research suggests women enjoy limiting opportunities to engage in income-generating activities (Manser & Brown, 1980) and financial decision-making in a household (Cole et al., 2015; Sholevar & Harris, 2020). A lack of agency regarding income and financial decision-making procedures can restrain the women from efficiently using the skills and cash obtained from multifaceted cash transfer programs to eradicate poverty from their households. In contrast, having agency allows women the choice to utilize the cash transfer in a way that would help their household climb out of poverty as they are the ones who, along with the cash transfers, also directly receive complementary interventions such as training and access to savings associations for utilizing the cash transfers efficiently. Hence, in the context of multifaceted cash transfer programs, this research argues that having the agency to participate in household income and financial decisions is a vital capacity for women. Therefore, I constructed the subdimension of agency with available questions regarding women's agency in income and financial decision-making within their household. I also included a question regarding visiting families and relatives in the subdimension of the agency. Existing literature confirms women's participation in decisions regarding visiting friends and family (Deere & Twyman, 2012). Nevertheless, I added that particular question to capture any trade-off that might occur if women experience a shift in financial and income-generating decision-making within their household.

Following the description provided above, to construct the subdimension of agency, I performed factor analysis on the following questions, and I predicted a factor score named 'agency' based on one factor with an eigenvalue of more than 1 (See ANNEX B, table 3).

A. Who usually makes decisions about making major household purchases?
B. Who usually makes decisions about visits to family or relatives?
C. Who usually decides how the money you earn will be used?
D. Who usually decides how your (husband's/partner's) earnings will be used?

The questions could be answered using the following options 1. myself, 2 . myself and husband or partner jointly, 3. partner or husband, 4. someone else in the family. The results of the factor analysis and the KMO test indicating acceptable consistency among the variables can be found in ANNEX B, table 3.

Financial Buffer: People in poverty face unexpected situations such as irregular employment, erratic work schedules, fluctuating public benefits, shifting household composition, frequent housing moves, and other changes that undermine their precarious finances (Campbell, 2016). Not having additional income to revive from such a phenomenon can further confine the poor into poverty, indicating that only considering sustenance while calculating the income needed to escape poverty is insufficient (Carter & Barrett, 2006). Hence, aligning with such an argument, I included daily savings as an indicator to reflect a person's financial capacity to cope with the unexpected phenomenon described above. I utilize the following questions to reflect the daily savings of the beneficiaries:

A. In total, how much money do you save per month?

B. In total, how much money do you save per week?

C. In total, how much money do you save per day?

I did not have sufficient observations for the three questions mentioned above. Therefore, I obtained the missing values in the variable 'sav,' which recorded the answer to question C (savings/day) by dividing the amount reported in question A (savings/month) by 30 and the amount reported in question B (savings/week) by 7, reflecting amount saved per day based on savings per month and week.

Additionally, I standardized the variable 'sav' and added it to the standardized dummy variable 'nocash' to generate the score for the financial buffer. The variable 'nocash' captured the answer to the question "Over the past month, how often did you or any member of the household go without cash?" (0 if nocash=always/sometimes, and 1 if nocash= rarely/ almost never), and therefore was included as it reflected the capacity of the beneficiaries to sustain financially. The following equation can explain the procedure:

(8) financialbuffer= z_(z_nocash+z_sav)

Finally, I created the dimension capacity by standardizing the summation of the standardized scores of 'financial buffer' and 'agency.' The formula to construct the dimension of capacity is as follows:

(9) capacity= z _(z_financialcoping+z_agency)

It is important to note that multifaceted cash transfer programs are proven to be efficient in increasing school attendance (de Brauw & Hoddinott, 2011; Millán et al., 2019). Education provides individuals with the basic knowledge and skills for strategic thinking (Malyan & Jindal, 2014), which makes it an important aspect of capacity (Alaerts & Dickinson, 2008). An increase in school attendance can act as a proxy of increase in education, making school attendance a crucial indicator to consider while constructing the dimension of capacity in the context of multifaceted cash transfer programs. Despite having question regarding school attendance in the monitoring and evaluation survey of 100WEEKs, due to insufficient observations available for the question, I did not include it in the dimension of capacity (elaborated in detail in Chapter 5). However, I strongly recommend that school attendance should be taken into account while constructing the dimension of capacity in future research.

Social Capital

Social Capital refers to the resources available to an individual due to his/her membership in a social network (Villalonga-Olives & Kawachi, 2015). To form the dimension of social capital, I performed factor analysis among four binary choice statements related to social connectivity, which were previously used in a study in Rwanda by Caeyers & Fuller (2015). The statements are as follows:

1. Other people in the community sometimes ask you to take care of their children (Yes/No)

2. You would be able to ask others in the community for advice or support if you needed it (Yes/No)

3. Other people in the community often ask you for advice or support when they need it (Yes/No)

4. You are usually invited if there is a celebration in the community. (Yes/No)

I retained the one factor which had an eigenvalue of more than 1. Afterward, I predicted the factor score as ‘socialcapital’. Further, I performed the Kaiser Meyer Olkin test (KMO) to check the internal consistency within the variables. The result was above 0.6, indicating an acceptable level (See ANNEX B table 4).

Income and Assets

The dimension of income and assets should include two subdimensions: income and assets. However, due to a lack of data regarding income, Chapter 3, only covers the subdimension of assets. The subdimension of income is constructed and evaluated in Chapter 4.

Assets: Asset refers to anything that can be owned and controlled to produce economic value (O’Sullivan, 2003). Based on available data, within this research, I formulated the subdimension of assets by performing factor analysis among all the variables that captured ownership of productive or income-producing assets. The factor analysis generated one factor with an eigenvalue of more than one. Thus, I predicted one factor score ‘asset’ to capture the subdimension of assets. I checked the internal consistency within the variables using the Kaiser Meyer Olkin test (KMO), and the result was 0.6, indicating an acceptable level (See ANNEX B table 4). The subdimension of assets included assets that are used to produce income in rural setups of Africa, such as sewing machines, land, housing, and farming tools such as a hoe, shovel, rake/spade, and pick (Devereux, 2016; Solotaroff et al., 2019).

Additionally, I included the question regarding ownership of bicycle, as in the agricultural context, bikes are productive assets because it helps with the transportation of goods (Wodon, 2007). Based on the same logic, I also added motorcycles as productive assets. Further, following the guidelines used by the International Livestock Research Institute, I constructed a score named tropical livestock unit that reflects the value of owning different live-stock animals per household (Njuki et al.,2011). Table 3 shows the values associated with owning each type of livestock animals. In the table, N=total number of the corresponding animal in a household, which ranges from 0, representing not owning the corresponding animal. The final tropical livestock score 'TLU' for each household was generated by summing up the scores calculated based on Table 3. Households possessing no animals were assigned 0.

Table 3: Tropical Livestock Unit Per Animal

Animal	TLU score
Goats	0.2*N
Sheep	0.2*N
Poultry	0.04*N
Rabbits	0.04*N
Donkeys	0.8*N
Horses	0.8*N
Pigs	0.3*N
Guinea Pigs	0.04*N
Cow	1.0*N
Bull	1.2*N

3.4 Hypotheses

Within this research, I aim to formulate the hypotheses based on existing literature and 100WEEKs intervention setup. According to Gobin and Santos (2015), the shortcomings of conditional and unconditional cash transfer programs have been taken into account in the multifaceted cash transfer program. Therefore, I assume multifaceted cash transfers will retain the impact of unconditional and conditional cash transfer programs on my dimensions of interest. Thus, the hypotheses are formulated based on the literature regarding multifaceted, conditional, and unconditional cash transfer programs.

Health: As described in section 3.3, I constructed the dimension of health with psychological health and nutrition. Cash transfer programs have mixed impacts on psychological health (Ohrnberger et al., 2020; Ohrnberger et al., 2020). 100WEEKs provides the beneficiaries with 8 euros/week. Providing money has shown to positively impact psychological health (Haushofer & Fehr, 2014). Moreover, the intervention of 100WEEKs has a feedback mechanism through which the beneficiaries can raise their concerns and problems if they have any. Therefore, if any beneficiary faces any stressful situation regarding the intervention, they can report it to 100WEEKs. 100WEEKs then addresses such concerns as part of their feedback mechanism, which should alleviate any stress-inducing factors caused by their intervention. The additional income combined with the feedback mechanism should result in positive psychological health outcome.

Nevertheless, 100WEEK’s beneficiaries are women, who, along with participating in the intervention, also have to tend to their daily duties (Baird et al., 2018). Such additional workload can cause stress which may result in negative psychological health outcome. Hence, I anticipate finding either positive or negative on psychological health in this research.

Furthermore, existing literature confirms that multifaceted cash transfer programs should have positive outcome in the subdimension of nutrition (García-Guerra et al., 2019). Additionally, 100WEEKs provides training on maintaining a nutritious diet to the beneficiaries. Therefore, I anticipate having a positive outcome on nutrition within this research. Thus, summing up the expected positive or negative impact on psychological health and positive effects on nutrition, within this research, I hypothesize that it is possible to have either positive or negative outcome in the dimension of health.

The impact on the dimension of health can be negative if I find a robust negative impact on the subdimension of psychological health outweighing the anticipated positive effects on nutrition. The impact on the dimension of health can be positive if I find a positive impact on the subdimension of psychological health combined with the anticipated positive outcome in the subdimension of nutrition. Also, I can find positive outcome in the dimension of health if the anticipated positive outcome in the subdimension of nutrition outweighs the possible negative impact on the subdimension of psychological health. It is also possible that the anticipated negative impact on the subdimension of psychological health offsets the expected positive outcome on nutrition, falsely indicating that a multifaceted cash transfer program has no effect on health. In such a case, I will examine the results of each subdimension to assess the impact of multifaceted cash transfer programs on health.

Living Standard: As per existing literature, cash transfer programs have proven to improve the beneficiary's material well-being and food security (Banerjee et al., 2015), which are the two subdimensions of living standard. Therefore, I hypothesize that 100WEEK's intervention, a multifaceted cash transfer program, positively impacts the beneficiaries' living standards.

Capacity: Banerjee and Duflo (2015) find multifaceted cash transfer programs similar to 100WEEKs positively impact decision-making in the short term. However, the impact does not sustain in the long run. As this research uses the data collected right after the intervention of 100WEEKs, I anticipate having a positive impact on the sub-dimension of agency. Moreover, cash transfer programs also increase savings and decrease monetary poverty (Banerjee et al., 2015). In addition, 100WEEK's intervention includes access to the village saving association of the beneficiaries, giving them access to an institutional setup for savings,which can lead to an increase in the beneficiaries' savings (Ksoll et al., 2016). Hence, I anticipate a positive impact on the subdimension of a financial buffer as well. Together with the forecasted positive impact on the subdimension of 'agency' and 'financial buffer' I hypothesize that 100WEEKs intervention positively impacts the dimension of capacity.

Social Capital: Cash transfer programs positively impact social capital (Attanasio et al., 2015; Attanasio et al., 2009). Further, one of the components of 100WEEK's intervention is providing the beneficiaries with training in groups which allows the beneficiaries to make meaningful social connections, as reported by the coaches who provide the training of 100WEEK's intervention. Therefore, this research hypothesizes that 100WEEK's intervention positively impacts social capital.

Assets: Based on previous literature, I hypothesize that 100WEEK's intervention has a positive impact on the subdimension of assets (Haushofer & Shapiro, 2018; Asfaw et al., 2014; Bastagli et al., 2019; Rigolini, 2016).

3. 5 Methodology to Assess Impact

After constructing the hypotheses, the next step is to assess the impact of the multifaceted cash transfer on the dimensions and subdimension. To assess such impact, it is essential to compare treatment groups who have finished participating in the multifaceted cash transfer program of 100WEEKs with a credible comparison group. However, this research uses secondary data from 100WEEK's database, which only contained surveys collected from 100WEEK's beneficiaries who have already received, or will eventually receive the intervention. 100WEEKs conducts several rounds of data collection to monitor and evaluate their intervention. The baseline data is collected before the beneficiaries start with their 100WEEK's program, and the endline data is collected right after the beneficiaries complete the 100WEEK's program. Further, when one group finishes the intervention, a new group is onboarded immediately. Hence, I had endline data of the beneficiaries who completed 100WEEK's intervention and baseline data of the beneficiaries who were about to start 100WEEK's intervention collected during the same days. Therefore, I decided to form a comparison group from the data of the groups whose baseline information was collected on the same day as the treatment group's endline data. Afterward, I used the method of propensity score matching (PSM) to estimate the impact of the multifaceted cash transfer program due to following reasons:

1. The beneficiaries of 100WEEK's intervention were not selected randomly. Hence there is selection bias within the sample. Selection bias is a problem as it can cause my results to be confounded due to possible unobserved factors that can affect my outcome of interest. For example, selection bias can occur when teachers, bureaucrats, or legislators

decide which person will receive the treatment (Guo & Fraser, 2015). 100WEEKs collaborates with local priests and coaches to select their beneficiaries, which can cause selection bias. However, in this research, I constructed the comparison group with beneficiaries chosen to receive the intervention of 100WEEKs. Therefore, it implies that they have already undergone a similar selection procedure as the treatment group, which to some extent addresses the issue of possible selection bias caused due to the process of beneficiary selection. Nevertheless, the beneficiaries in the treatment and the comparison group participate in the intervention during different time periods. Beneficiaries selected to participate in the intervention earlier (treatment group) may differ from participants selected later (comparison group), which can be a source of selection bias.

2. The monitoring and evaluation survey questionnaire of 100WEEKs evolved over time. Therefore, despite collecting baseline and endline data from every beneficiary enrolled in 100WEEK's program, information regarding all the indicators necessary for this research was unavailable for the same beneficiaries during both rounds. Hence, I had to choose a suitable method in a setup where data for only one round was available.

Propensity Score Matching (PSM) utilizes data collected during one round to compare similar participants between the treatment and comparison groups for impact assessment and also tackles selection bias. PSM addresses selection bias by generating propensity scores that reflect the probability of being treated for each observation in my sample. While calculating the scores, variables reflecting pre-treatment characteristics that are known to be related to the treatment and the outcome of interests are taken into account to satisfy the conditional independence assumption[11], therefore addressing the issue of selection bias. The variables reflecting

[11] The conditional independence assumption states that, after conditioning on a set of observed covariates, treatment assignment is independent of potential outcomes (Masten & Poirier, 2017).

pre-treatment characteristics are also known as co-variates. The following equation can express propensity scores:

$$(10)\ p(X) = pr(D = 1|\ X)$$

Where D {0,1} is a variable that captures treatment status (treated=1 and untreated=0) and X is a multidimensional vector that represents the covariates. To ensure that the covariates reflect the pre-treatment characteristics of the beneficiaries, it is best to choose the covariates based on previous research and scientific findings (Rubin, 2001). Previous research has found that poverty in Rwanda is influenced by age, level of education attained, province of residence, number of household members, partnership status, and number of children who attend school (Bizoza et al., 2018; Cho & Kim, 2017). Additionally, as the sample size I used is collected over a time span of 17 months, I also matched participants based on the day on which their data was collected to capture any possible determinants of poverty that could vary over time. Therefore in this research, I used the following variables as covariates:

Table 4: Covariates

Name of the Variable	**Description of Variable**
age_1	Age of the participant
Schoolatt	Highest level of school that is attended by the woman (0 = preprimary, 1 = primary, 2 =secondary, 3 = tertiary)
Partner	Presence of a partner in the households (1 = Husband who lives in the same household, 2 = Partner who lives in the same household, 3 = No husband or partner, 4 = Husband who does not live in the same household, 5 = Husband has died, 6 = Partner does not live in the same household)
schoolagedchildren	Number of school aged children (aged between 7 and 14) within the household
howmanyhhm	Please tell us how many other household members your household has

Location	District of residence: Musanze=1, Gakenke=2, Burera=3, Rulindo=4, Nyabihu=5, Muhange=6
endate	The date of data collection ranges from 2020-06-18 to 2022-01-25. The dates were stored as string variables and were transformed into 8-digit numeric variables by excluding the character '-'.

Based on the chosen covariates, propensity scores were generated for each participant of the treatment and comparison groups using a logit or a probit model. Afterward, participants having similar propensity scores between the treatment and comparison group were compared to find the impact of the treatment on the outcomes of interests which can be expressed through the following equation:

$$\textbf{(11)}\ D(i, j) = |\ ei - ej|\ or\ \textbf{(2)}\ D(i, j) = |logit(ei) - logit(ej\ )|$$

Where ei refers to the propensity score of the participants of the comparison group and ej refers to the propensity score of the treated participants.

One caveat of propensity score matching is that it derives the impact on the outcome of interest by comparing participants who possess similar propensity scores between the treatment and comparison group. The propensity scores are constructed with available pre-treatment characteristics that I can use as covariates. Nevertheless, there is a possibility; that despite having similar propensity scores, participants might differ based on unobserved characteristics. In a hypothetical scenario, if I had compared beneficiaries who completed 100WEEKs intervention to non-beneficiaries who did not receive 100WEEKs intervention, there could be a possibility that my outcome of interest is confounded by unobserved intrinsic behavioural differences between the two groups. It is because participants participating in an intervention that includes weekly training for 100 weeks might have motivational/aspirational differences compared to non-participants who did not participate in such a rigorous intervention. In such a scenario, using PSM to compare the participants and non-participants can generate biased results due to unobservable factors like aspiration/motivation. However, within this research, the possibility of the results being confounded by unobservable factors like aspiration is tackled by constructing the comparison group with participants who will eventually enroll in 100WEEKs program. Therefore, they are more likely to be similar to the treatment group participants compared to non-participants who do not enroll in the intervention at all.

3.6 Results and Discussion

The section on Results and Discussion will contain an overview of the matching quality between treatment and comparison groups, followed by the analysis of the results and discussion.

3.6a Matching quality

Before diving into the results of the propensity score matching, it is crucial to assess whether the matching eliminated the differences between the treatment and comparison groups. Hence, I conducted a t-test among the covariates of propensity score matching to evaluate the balance among the treatment and comparison groups reported in Table 5. From the table, it can be seen that all the covariates were not balanced before matching. However, after matching, all the variables included as covariates show insignificant p-values, indicating a reduction in bias.

Table 5: Matching Quality

Variable	**Mean**			**%reduct**	**t-test**	**V(T)/**
	Treated	Comparison	%bias	bias	t (p>t)	V(C)
schoolatt U	2.4565	2.42	4.1		0.55 (0.584)	1.13
M	2.4438	2.5375	-10.5	-156.7	-1.27 (0.205)	0.90
howmanyhhm_1 U	4.0311	3.625	26.0		3.48 (0.001)**	1.03
M	4.0156	4.0938	-5.0	80.8	-0.54 (0.586)	0.59*
age_1 U	33.596	31.825	32.9		4.40 (0.000)***	1.10
M	33.534	33.669	-2.5	92.4	-0.32 (0.749)	1.14

partner U	1.1335	1.14	-1.2		-0.16 (0.874)	0.94
M	1.1344	1.0719	11.6	-867.5	1.82 (0.069)	3.11*
schoolagedchildren U	1.2019	1.0175	18.9		2.53 (0.012)**	0.97
M	1.1969	1.175	2.2	88.1	0.27 (0.784)	0.86
endate U	2.0e+13	2.0e+13	-52.0		-7.03 (0.000)***	1.52*
M	2.0e+13	2.0e+13	-11.3	78.3	-1.41 (0.160)	1.44*
location U	1.6584	2.16	-40.7		-5.29 (0.000)***	0.32*
M	1.6625	1.5875	6.1	85.0	0.98 (0.326)	0.65*

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

Moreover, the chi-square test in the logit model displayed in Table 6 was rejected before matching (prob > X 2 = 0.000). In contrast, after matching, the chi-square test reported a value of 0.155, which is more than 0.05, indicating all the variables are not jointly significant at a 5% significance level. Consistently, the pseudo R^2 of the model is lower after matching (0.011)than before matching (0.108), indicating no systematic differences between the treatment and comparison groups.

Table 6: Chi-Square Test and Pseudo R2 Test of Matching

Sample	Ps R2	LRchi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.108	107.58	0.000***	25.1	26.0	81.2*	1.37	29
Matched	0.011	9.35	0.155	7.0	6.1	24.0	1.73	57

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

Consequently, only two observations among the sample, as shown in Table 7 appears to be off-support, indicating adequate overlap of propensity scores among treatment and comparison groups. Consistently, the histogram in Figure 2 displays adequate common support as well. Therefore, I can conclude that propensity score matching successfully created a counterfactual similar to the treatment group.

Table 7: Participants off Support

SUPPORT	TREATED	COMPARISON
ON	320	400
OFF	2	0
TOTAL	322	400

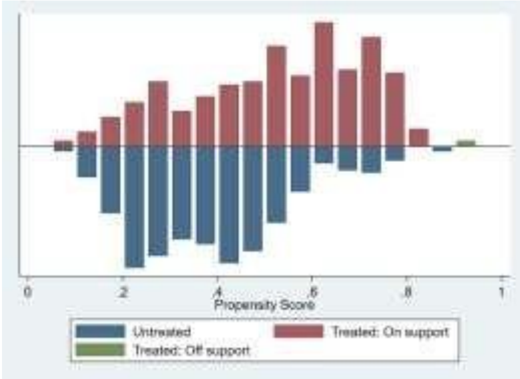


Figure 2: Histogram Displaying Common Support

3.6b Treatment Effects

This research employs the method of nearest neighbour matching[12] to match participants among treatment and comparison groups. As matching was done only among participants within the range of common support[13] , 320 participants in the treatment group and 400 participants in the comparison group were compared to estimate the average treatment on the treated (ATT). Two participants in the treatment group who were off support were dropped during the procedure.

As the results of propensity score matching can be scrutinized due to the existence of potential unobservable factors, I also present results obtained from the method of OLS regressions simultaneously to check the robustness of the obtained outcome. I first conducted naive OLS regressions for each of the dimensions and subdimension where the respective dimensions and subdimension of assets were included as dependent variables, and the dummy variable T, which captured the completion of 100WEEK's program, was included as the independent variable. However, as the sample is not randomly selected, and there is a presence of selectionbias, the naive regression mentioned above provides a less precise estimate of the influence of

[12] Several methods to match participants in treatment and comparison group exists. However, none of the methods is superior to the others (Baser, 2006). Within this research, I employ nearest neighbour matching. It involves running through the list of treated units and selecting the closest eligible comparison unit to be paired with each treated unit. Later I utilize the Rosenbaum sensitivity analysis to observe whether any hidden bias affects the detected results.

[13] Common Support range is constructed based on similar propensity scores between treatment and comparison groups. Participants who are off support in the treatment group do not have similar propensity scores to the participants in the comparison group. If I include the participants who are off support, I might end up comparing very different participants across treatment and control group, which can cause bias in our results.

100WEEK's program on my outcome of interest. Therefore, I further re-conduct OLS regressions for each dimension and subdimension, where along with the dummy variable T, I included the covariates mentioned in section 3.5 as control variables. I did so to account for the influence of the covariates on the five dimensions and obtain a more precise estimation of T.

Additionally, I find it necessary to mention that within this research, I standardized all the subdimensions and dimensions so that the obtained results are derived as changes in standard deviation and are comparable to each other.

Table 7 displays the OLS coefficients and the Average Treatment Effect on the Treated (ATT) on the four dimensions of health, living standard, social capital, capacity, and the subdimension of assets. Consistent with my hypothesis, the impact of a multifaceted cash transfer program is shown to have a significant positive impact on the dimensions and subdimension mentioned above.

Firstly, both OLS (with and without controlling for covariates) and PSM suggest that participation in the multifaceted cash transfer program of 100WEEKs appears to positively impact the beneficiary's health at a 1% significance level (See Table 7). The naive OLS coefficient without covariates as controls suggests that, on average, the treatment group's outcome for the dimension of health is 0.61 standard deviation greater than the comparison group. Similarly, the coefficient obtained from OLS with control variables suggests that, on average, the treatment group has 0.58 standard deviation higher outcome on the dimension of health compared to the comparison group. Additionally, the ATT indicates that, on average, the dimension of health between the treatment and comparison groups differ by 0.58 standard deviation.

Secondly, participants of the 100WEEK's intervention show significant improvement in the dimension of living standard compared to the comparison group. As shown in the second row of Table 7, the naive OLS coefficient without controls suggests that, on average, the treatment group's outcome for the dimension of living standard is 1.33 standard deviation greater compared to the comparison group. Similarly, the coefficient obtained from OLS with control suggests that, on average, the treatment group has 1.34 standard deviation higher score on the dimension of living standard compared to the comparison group. Additionally, the ATT suggests that, on average, the treatment and comparison group differs by 1.33[14] standard deviation on the dimension of living standard. The results are significant at a 1% level.

Thirdly, participating in 100WEEK's intervention shows a significant increase in the dimension of capacity. The naive OLS coefficient without covariates as controls suggests that, on average, the treatment group's score for the dimension of capacity is .71 standard deviation greater compared to the comparison group. Similarly, the coefficient obtained from the OLS with control variables suggests that, on average, the treatment group has .72 standard deviation higher outcome on the dimension of capacity compared to the comparison group. Additionally, the ATT indicates that, on average, the treatment and comparison group differs by .77 standard deviation on the dimension of capacity. The results are significant at a 1% level.

Fourthly, participants in 100WEEK's intervention have significantly higher social capital than the comparison group. The naive OLS coefficient without covariates as controls suggests that, on average, the treatment group's outcome for the dimension of social capital is .31 standard deviation greater compared to the comparison group. Similarly, the coefficient obtained from the OLS with control variables suggests that, on average, the treatment group has .32 standard deviation higher outcome on the dimension of social capital compared to the comparison group.

[14] It is crucial to mention that due to the presence of selection bias, OLS regression cannot derive causal relationship between treatment and the dimensions and subdimension. Propensity score matching, on the other hand tries to tackle selection bias through matching the treatment and comparison groups on the basis of covariates, and derive causal results between the treatment and the dimensions. However, for the dimension of health and living standard, I almost see similar results for both OLS and PSM , which makes me critical regarding whether PSM was really successful in addressing the selection effects.

Additionally, the ATT suggests that, on average, the treatment and comparison group differs by .50 standard deviation on the dimension of social capital. The results are significant at a 1% level.

Lastly, as shown in Table 7, participation in the 100WEEK's multifaceted cash transfer program leads to higher productive assets. The naive OLS coefficient without covariates as controls suggests that, on average, the treatment group's score for the subdimension of asset is 1.18 standard deviation greater compared to the comparison group. Similarly, the coefficient obtained from the OLS with control variables suggests that, on average, the treatment group has a 1.15 standard deviation higher score on the subdimension of assets than the comparison group. Additionally, the ATT indicates that, on average, the treatment and comparison group differs by 1.22 standard deviation on the subdimension of assets. The results are significant at a 1% level.

Table 7: Treatment Effect Per Dimension

Dimensions	OLS (without control)	OLS (with control)	Propensity Score Matching (ATT)
Health	.6095706 (0.000)***	.5764972 (0.000)***	.576864973 (0.000)***
Living standard	1.332575 (0.000)***	1.347896 (0.000)***	1.333 (0.000)***
Capacity	.7133341 (0.000)***	.7203997 (0.000)***	.771312718 (0.000)***
Social Capital	.3104839 (0.000)***	.3226406 (0.000)***	.506345478 (0.000)***
Asset	1.184954 (0.000)***	1.149598 (0.000)***	1.22711314 (0.000)***

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

To investigate the results further, I will refer to the effect of 100WEEK's intervention on each subdimension (See Table 8).

The dimension of health was constructed with subdimensions of nutrition, and psychological health. From Table 8, it can be seen, participants of 100WEEKs display significantly higher nutrition outcome compared to the comparison group. 100WEEK's training includes sessions on the benefits of consuming diverse food groups and the importance of a nutritious diet. Further, 100WEEKs also provide financial means that can be used to obtain a nutritious diet. The training together with financial means can be the possible explanation for significant improvement in the subdimension of nutrition.

Interestingly, from both the results of OLS and PSM, I find 100WEEK's intervention has a negative impact on the beneficiaries' psychological health, which is significant at a 1% level. The beneficiaries of 100WEEK's intervention are women who, along with participating in 100WEEK's intervention, might also have to attend to their household chores and responsibilities assigned to them due to their gender roles, which can make them unable to enjoy leisure due to additional workload (Baird et al., 2018). Therefore, the increased workload on the women could be the possible reason for the negative psychological health outcome. Further, the data used in this research is collected right after the completion of 100WEEK's intervention, when the beneficiaries stop receiving the cash transfers provided by 100WEEK. Therefore, the negative shock in their income could also be the reason for the negative outcome in the subdimension of psychological health.

Such outcome in the subdimension of psychological health stresses the need to address the adverse effect of 100WEEK's program through complementary interventions such as psychological health support services and also indicates the need for future research so that the mechanism behind the negative outcome can be identified.

Nevertheless, the robust improvement in the subdimension of nutrition seems to outweigh the negative impact on psychological health, which led to a significant positive outcome in the dimension of health.

The dimension of the living standard was constructed using two sub-dimension, namely, material wellbeing and food security which captured access to food. Table 8 shows a significant positive impact of 100WEEK's intervention on both subdimensions. The possible explanation behind such a result can be straightforward. The additional income obtained through cash transfers enabled the beneficiaries to invest in their material well-being and food consumption, therefore combinedly improving their living standard.

Within this research, capacity consisted of two subdimensions; agency, constructed based on the women's decision-making power, and financial buffer; constructed based on savings and the capacity to sustain financially. As displayed in Table 8, OLS results show that the subdimension of the agency is negatively associated with receiving the intervention of 100WEEKs. The result is significant at a 5% level. Such a result contradicts the existing literature, which suggests that participating in multifaceted cash transfer programs positively influences the beneficiary's agency (Banerjee et al., 2015). Therefore, there is a need to further investigate the mechanism behind the obtained negative outcome. However, I need to recognize that the OLS results within this research only provide a correlation between agency and treatment status due to selection bias between the treatment and comparison groups. Propensity score matching tries to tackle the selection biases by matching the beneficiaries from the treatment and comparison groups based on the covariates mentioned in section 3.5. The average treatment on the treated (ATT) generated from PSM also shows participation in 100WEEK's program negatively affects beneficiaries' agency. Nevertheless, due to the insignificant p-value (>0.05), I fail to conclude that the mean difference in agency between the treatment and comparison group is statistically different than 0.

Contrarily, I find that participation in the 100WEEKs program positively affects the subdimension of the financial buffer. The results are significant at a 1% level. The training sessions of 100WEEKs include modules on entrepreneurship skills that could help beneficiaries sustain themselves financially. Further, the beneficiaries had access to village savings accounts (VSLAs) which could inspire the beneficiaries to save more. Training sessions, together with VSLAs could explain the positive outcome in the subdimension of the financial buffer. Although the effect of a multifaceted cash transfer program on the agency is debatable (as I find different results from PSM and OLS), the significant positive outcome in the subdimension of the financial buffer can explain the positive outcome in the dimension of capacity.

The dimension of social capital had no subdimensions. Beneficiaries of the 100WEEKs intervention receive weekly training in groups for 100 weeks. The training includes vigorous interactive group work and fun activities as well. Hence, the participants have the opportunity to create a meaningful bond with each other. Moreover, the training includes a module that particularly addresses the negative impact of jealousy among social groups. Therefore, the opportunity for social interaction, together with the training against jealousy, can be the possible reason behind the higher social capital of the beneficiaries.

The subdimension of assets was constructed using questions regarding ownership of productive assets. Similar to the dimension of living standard, the possible explanation behind such a result could be the translation of additional income into productive assets.

Table 8: Results per Subdimension

Dimensions	**Sub-dimensions**	**OLS(without control)**	**OLS (with control)**	**Propensity Score Matching (ATT)**
Health	**Nutrition**	1.507261 (0.000)***	1.493459 (0.000)***	1.49966718 (0.00001)***
	Psychological health	-.8395431 (0.000)***	-.8619689 (0.000)***	-.865187557 (0.00001)***
Living Standard	**Material Wellbeing**	.4657897 (0.000)***	.4659589 (0.000)***	.38476518 (0.001309)***

	Food Security	1.624914 (0.000)***	1.648783 (0.000)***	1.70571986 (0.00001)***
Capacities	**Agency**	-.1682189 (0.025)**	-.1536884 (0.023)**	-.031947869 (0.39746)
	Financial Buffer	1.175467 (0.000)***	1.170913 (0.000)***	1.12850157 (0.0001)***

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

3.7 Robustness Check

This section of the paper will check the robustness of the results mentioned above.

3.7a Sensitivity Analysis

Despite being a popular methodology for impact assessment, propensity score matching has been widely criticized in academia as it can produce biased results when participants in treatment and comparison groups are wrongly matched (King & Nielsen, 2019; Baser, 2006). Hence, I performed Rosenbaum sensitivity analysis to check whether a given level of hidden biases can affect the average treatment effect (Gangl, 2004). The Rosenbaum sensitivity analysis confirmed significant results if the bias level is increased to 200% for the dimension of living standard, social capital, capacity, and assets. For the dimension of health, the result remained significant till bias was increased up to 100%; therefore confirming that even if there are hidden biases at least up to 100% for health and 200% for other dimensions and subdimension, I will get significant results in all five dimensions. The results of the sensitivity analysis per dimension are attached in ANNEX C.

3.7b Multiple Hypotheses Testing

Testing for multiple hypotheses at once increases the chance of generating false-positive results[15]. In my analysis mentioned above, I tested five hypotheses. Hence, to address such concern, I applied Anderson's code (2008) for calculating sharpened q-values to generate false

[15] A false positive shows statistically significant effect, even if there is no effect.

discovery rates. The sharpened q value for each dimension is less than 0.05, indicating the probability of getting false positive results is less than 5% and is statistically insignificant. The results of the multiple hypothesis testing are attached in Table 9.

Table 9: Sharpened q values

p-value	Sharpened q value
0.0001	0.001
0.0001	0.001
0.0001	0.001
0.000213	0.001

Chapter 4: Treatment Effect on Income

Due to insufficient data, Chapter 3 could not take the subdimension of income into account. However, income is one of the primary measurements and is an essential aspect of poverty (Schenck-Fontaine & Panico, 2019). Thus, Chapter 4 is dedicated to assessing the influence of multifaceted cash transfer programs on the subdimension of income. The Chapter includes data source, hypothesis, methodology, results, and discussion of the procedure.

4.1 Data Source and Sampling

Throughout their participation in the intervention of 100WEEKs, beneficiaries receive a financial diary where they are encouraged to note their income, expenditure, and savings per week during the period of participating in the intervention. The purpose of the financial diary is to help participants keep track of their financial transactions. 100WEEKs also records the data from the financial diary in excel sheets for each participant to monitor and evaluate their financial condition. Although participants receive training on filling out the financial diaries, according to the 100WEEK's team, a low literacy rate among the participants makes it harder for the beneficiaries to fill out the financial diaries consistently. Also, as reported by the 100WEEKs team, storing the data in excel sheets is time-consuming. Therefore, it is difficult to maintain a digital version of the financial diary for all the participants. Due to the reasons mentioned above, 100WEEKs could only provide panel data on income, expenditure, and savings gathered during the 90th to 100th week (last 10 weeks) of 100WEEKs intervention from 128 participants.

After obtaining the data from 100WEEK's team, I calculated each beneficiary's income by subtracting their business investment from the total amount earned per week to reflect the actual income they earned during the 90th to 100th week (last 10 weeks) of the intervention. Afterward, I generated the mean and median of the income obtained between the 90th to 100th week for each beneficiary. The variables were named 'mean_income' and 'median_income,' respectively. The variable 'mean_income,' which captured the mean of income, provided the average amount of money earned by each beneficiary during the last 10 weeks of the intervention. The variable 'median_income,' which captured the median of income, provided us the amount in the middle of the income distribution earned by each beneficiary during the last 10 weeks of the 100WEEKs intervention.

Poverty is associated with volatile income (Ridley et al., 2020). Volatile income refers to having a sharp decline and increase in income over time (Ridley et al., 2020). 100WEEKs targets poor women as beneficiaries. Therefore, a participant might earn a lot in one week but might not earn anything the next. However, the mean of income would generate the summation of income obtained from all the weeks divided by the number of weeks and would fail to capture any fluctuation. Therefore, to tackle such an issue, as suggested in the existing literature, I also generated the median of income for each beneficiary (Chiripanhura, 2011). Median of income provides the amount at the midpoint of the income distribution of each beneficiary and is not impacted by income fluctuation of the poor. Therefore, analyzing both mean and median income would capture a more holistic understanding of the beneficiaries' income.

4.2 Hypothesis

Income: According to the results derived in Chapter 3, 100WEEK's intervention has a significant positive impact on health, living standard, social capital, capacity, and also on the subdimension of assets. Addressing constraints in multiple dimensions of poverty has shown to efficiently eradicate poverty overall (Gobin and Santos, 2015). Hence, I deduce the positive impact on the dimensions and subdimension mentioned above should also address monetary poverty and positively influence income. Therefore, this research hypothesizes that beneficiaries receiving 100WEEKs intervention should have higher mean and median of income than the comparison group.

4.3 Methodology

Table 10 shows the available data from the financial diaries of the participants and the respective groups to which they belong. All 128 data points displayed in the table are obtained from the treatment group; no information was available on the comparison group. However, to analyze how a multifaceted cash transfer program influences the subdimension of income; I also needed data from the comparison group.

Table 10: Available financial diaries

Group	Freq.	Percent	T
RWA009	1	0.78	1
RWA010	9	7.03	1
RWA011	16	12.50	1
RWA012	14	10.94	1
RWA013	15	11.72	1
RWA015	16	12.50	1
RWA016	1	0.78	1
RWA017	14	10.94	1
RWA018	19	14.84	1
RWA020	16	12.50	1
RWA021	1	0.78	1
RWA023	5	3.91	1
RWA024	1	0.78	1
Total	128	100.00	

Therefore, this section of the paper will describe the method used to tackle missing data on the income of the comparison group, followed by the methodology used to assess the influence of multifaceted cash transfer programs on income.

4.3a Missing data

The dimensions of poverty are interrelated (Khan, 2019). According to Gobin and Santos (2015), addressing multiple constraints of the poor can help them "graduate from poverty" overall, indicating that impacting several dimensions of poverty can address the deprivations in all the dimensions of poverty. Income is an undebatable dimension of poverty (Schenck-Fontaine & Panico, 2019). Therefore, I assume that the positive impacts on the dimensions and subdimension, found in Chapter 3, is positively related to the subdimension of income as well. Thus, the data regarding the mean and median of income generated for each of the 128 beneficiaries were merged with participants in the main sample of 722 beneficiaries based on their group numbers and names. Afterward, I regressed[16] the mean and median of income earned by the beneficiaries throughout the 90th to 100th week of 100WEEKs on the generated scores of health, living standard, asset, social capital, and capacity. Apart from the dimensions and subdimensions specified above, variables regarding partnership status, age, the highest level of education attained, number of school-aged children, number of household members, and occupation of each beneficiary were also added as control variables as they are related to income (Stryzhak, 2020; Espenshade et al., 1983; Gustafsson & Johansson, 1999). I must mention that the VIF test results were 2.07 for both regressions indicating the absence of multicollinearity (SEE ANNEX E).

Afterward, the mean and median of income earned during the 90th and 100th week by each participant in both treatment and comparison groups were predicted using the inbuilt post-estimation command 'predict' in STATA, which calculated the fitted values by using the average effect of the absorbed variables using the following formula:

$$(12)\ Y_j = X_j b + d_{absorbedvar} + e_i$$

In the given equation, Y_j is the predicted income, $X_j b$ is the fitted value calculated based on the average effect of the absorbed variable, $d_{absorbedvar}$, includes the individual effects of the absorbed variables, and e_i is the error term in the predicted values.

[16] Regression studies the relationship between the dependent variable independent variables (Schneider et al., 2010)

I should point out that the regression performed with the raw variable of 'mean_income' as a dependent variable and the dimensions as independent variables displayed an R-squared value of 0.10, indicating that the regression model could explain 10% of the variability observed in the mean of income. Contrarily, a similar regression that was run with the log transformation of the 'mean_income' as the dependent variable and the subdimensions as the independent variable displayed an R-squared value of 0.30, which indicated that the regression model could explain 30% of the variation observed in the log transformation of the mean of income. The R-squared values indicated that the regression model, which used the log transformation of 'mean_income', could better predict the mean of income compared to the regression model, which only used the raw variable. Therefore, I used the regression model with the log transformation of 'mean_income' as the dependent variable to predict the log transformation of the mean of income for the entire sample. For the same reason of being able to describe more variation in the dependent variable, I used the regression model with the log transformation of 'median_income' as the dependent variable to predict the log transformation of the median of income for all the 722 participants in the sample. (The regression results, including the values of R-squared, are attached in ANNEX E).

4.3b Methodology to Assess Influence and Results

After addressing the issue of missing data, I wanted to determine the influence of 100WEEK's intervention on the subdimension of income. Therefore, I regressed the predicted log transformation of the mean and median of income on T, a dummy variable indicating whether the participant has completed 100WEEKs intervention. Apart from T, variables regarding partnership status, age, and the highest level of education attained, number of school-aged children, and number of household members were also controlled, as they are related to income (Stryzhak, 2020; Espenshade et al., 1983; Gustafsson & Johansson, 1999). From the results in Table 11, I can see that, on average, the treatment group has around 68% higher predicted mean of income than the comparison group. The results are significant at a 1% level. Similarly, Table 12 suggests that, on average, the median income of the participants in the treatment group is around 53.2% higher compared to the comparison group. The results are significant at a 1% level.

Table 11: Regression of Predicted Mean Income

ln_meanincomehat	Coef.	Std. Err.	T	P>t	[95% Conf.	Interval]
T	.685086	.0338842	20.22	0.000***	.6185604	.7516115
Schoolatt	.0486501	.0184795	2.63	0.009**	.0123689	.0849313
howmanyhhm_1	.0335736	.0146926	2.29	0.023*	.0047274	.0624198
age_1	-.0121674	.0039549	-3.08	0.002**	-.0199321	-.0044027
Partner	.1443635	.0281735	5.12	0.000***	.0890498	.1996772
Schoolagedchildren	.0382477	.0230836	1.66	0.098	-.0070728	.0835683
Endate	9.61e-11	2.62e-12	36.63	0.000***	9.09e-11	1.01e-10
Location	-.374636	.0121318	-30.88	0.000***	-.3984547	-.3508174
_cons	-1930.162	52.99046	-36.42	0.000***	-2034.2	-1826.125

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

Table 12: Regression of Predicted Median Income

ln_medianincomehat	Coef.	Std. Err.	T	P>t	[95% Conf.	Interval]
T	.532739	.0250135	21.30	0.000***	.4836295	.5818486
Schoolatt	.0370346	.0136417	2.71	0.007**	.0102516	.0638176
howmanyhhm_1	.0188773	.0108461	1.74	0.082	-.0024171	.0401718
age_1	-.0155079	.0029195	-5.31	0.000***	-.0212399	-.009776
Partner	.1011519	.0207979	4.86	0.000***	.060319	.1419848
Schoolagedchildren	.0540275	.0170405	3.17	0.002**	.0205716	.0874834
Endate	1.06e-10	1.94e-12	54.84	0.000***	1.02e-10	1.10e-10
Location	-.2930876	.0089558	-32.73	0.000***	-.3106707	-.2755045
_cons	-2134.117	39.11787	-54.56	0.000***	-2210.918	-2057.316

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

Despite being aware that the predicted mean and median of income are generated based on regressions models in section 4.3a, which could not explain 70% variation in the mean and 64% variation in the median of income earned by the beneficiaries, I still got curious to see the difference in the amount of predicted income earned by beneficiaries between the treatment and comparison group. Therefore I generated the mean scores of the predicted log transformation of the variable 'mean_income' and 'median_income' for the treatment and comparison groups separately.

Table 13: Mean and Median Scores of Treatment vs Comparison group

Mean and Median of Treatment group					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
ln_mean~t	322	10.85921	.7472265	8.932484	13.20612
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
ln_median~t	322	10.64121	.754388	8.875128	12.92079
Mean and Median of Comparison group					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
ln_mean~t	400	10.31001	1.019223	6.862384	11.95354
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
ln_median~t	400	10.27408	.934471	7.458669	11.86882

Afterward, I utilized the formula of inverse log function, which can be expressed by $e^{\ln(x)}$ to transform the log transformation of the predicted mean and median of income into actual amounts in Rwandan Franc. For the treatment group, the average predicted mean of income is 52000.05 Rwandan Franc per week, which equals 50.63[17] USD (See Table 14).

Table 14: Differences in Mean and Median of Income

Variable	**Treatment**	**Comparison**	**Difference**
ln_meanincomehat	10.859	10.310	0.549
ln_medianincomehat	10.641	10.274	0.367
Mean income (RWF)	52000.05	30031.437	21968.613
Mean income (USD)	50.63	29.24	21.39
Median income(RWF)	41814.565	28969.534	12845.031
Median income(USD)	40.72	28.21	12.51

[17] 100 Rwandan Franc=0.097 USD converted on 13-07-2022 (World Data, 2022)

The average predicted mean of income for the comparison group is 30031.437 per week, which is equivalent to 29.24 USD. On average, the mean of income of the treatment group is 21968.613 or 29.39 USD more than the comparison group. Following the same method, I find the average median of income of the treatment group is 41814.565 Rwandan Franc, or 40.72 USD per week, and the average median of income of the comparison group is 28969.534 Rwandan Franc or 28.21 USD. On average, the median of income of the treatment group is 12845.031 Rwandan Franc or 12.51 USD more than the comparison group.

Further, I also got curious whether the differences in the results were statistically significant when I compared the treatment group with a comparison group. Hence, as described in section 4.3a, I utilized the method of propensity score matching to assess the impact of 100WEEK's intervention on the predicted log transformation of the mean and median income. The results of propensity score matching in Table 15 display that participating in the intervention of 100WEEKs has a significant positive impact on the predicted mean and median of the beneficiaries' income.

Table 15: Results of the Subdimension of Income

Variable	Treated (T=1)	Comparison (T=0)	Difference	T-stat
ln_mean_Income	10.8643815	10.273009	.591372502	5.37 (0.001805)***
ln_median_Income	10.6459626	10.2196893	.426273371	4.12 (0.001309)***

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

Additionally, I conducted Rosenbaum sensitivity analysis to see if any hidden bias affected the results. The Rosenbaum sensitivity test reveals that the mean and median income results will remain significant at a 5% level if bias among treatment and comparison groups is increased up to 50%. The results for the median of income would remain significant at a 5% level if bias is increased up to 40% (See ANNEX D). It should be mentioned that I only focus on the positive side (sig+) of the test as I hypothesized to see an increase in income. Lastly, as I was testing to find an increase in the two outcomes, namely, mean and median of income, I also performed multiple hypothesis testing to detect the probability of getting false positive results. The sharpened q value obtained from multiple hypotheses testing was less than 0.01 (See Annex D), indicating that the probability of getting false positive results for both outcomes is statistically insignificant.

To explore the possibility of whether the positive results regarding income can also be extrapolated to the actual log transformation of median income, I inspected the correlation between the log transformation of mean and median income predicted for 722 participants in the sample and the actual log transformation of mean and median of the 128 participants obtained from the financial diaries. I found a high positive correlation of 55% between the log transformation of the actual mean and the predicted mean of income. Similarly, I found a positive correlation of 60% between the actual median and the predicted median of the income (See Table 16). Therefore, I find it safe to conclude that the actual income of the beneficiaries also has a high possibility of being influenced by the intervention of 100WEEKs. Likewise, the scatter plots between the log transformation of actual mean and median of income and the predicted mean and median of income show a positive ascending pattern indicating that the actual mean and median of income and the predicted mean and median of income are indeed positively correlated (see Figure 3). Nevertheless, due to insufficient data, I fail to determine the accuracy of the impact of multifaceted cash transfer programs on the actual income of the beneficiaries.

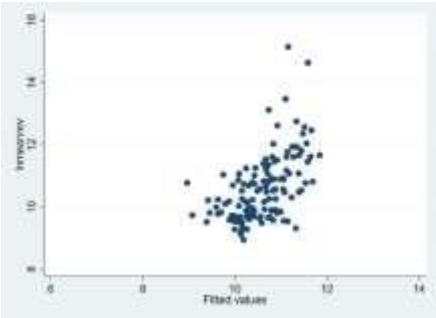
Table 16: Correlation Results

Correlation results: Mean income		
	ln_meanincome	**lnmean~t**
ln_meanincome	1.0000	
ln_mean~t	0.5554	1.0000

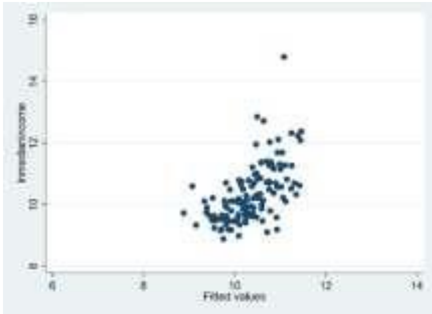
Correlation Results: Median Income		
	ln_median~e	**ln_median~t**
ln_medianin~e	1.0000	
ln_median~hat	0.5937	1.0000

Figure 3: Scatter Plots

Scatter Plot Real Mean Income vs Predicted Mean Income



Scatter Plot: Real median income vs predicted median income



4.4 Discussion

I find participating in 100WEEK's intervention can possibly lead to a significant increase in the beneficiaries' mean and median amount of income.

A probable mechanism for the increase in the mean and median of income was explored through multinomial logistic regression. I anticipated that the cash and training provided by 100WEEKs could give the participants the financial means and capacity to migrate into their preferred occupation. Such migration could be a possible reason behind the increase in income.

To perform the multinomial logistic regression, I divided the occupation based on the occupation groups mentioned in Table 17. The detailed occupations allocated per occupation group can be found in ANNEX F. The multinomial logistic regression reported in Table 2 of ANNEX F generated the probability of belonging to the occupation groups listed in Table 17 based on treatment status, the highest level of school attendance, age, partnership status, number of school-aged children, number of household members, district of the beneficiary, child mortality, and the day of data collection, as these factors are related to occupation attainment

Table 17: Occupational Groups

Occupation Group	Occupation Type
1	Occupations that are paid on a daily basis
2	Occupations that are slightly entrepreneurial
3	Agricultural occupation on own land
4	Occupations that are entrepreneurial
5	Agricultural occupation on rented land

of an individual (Rahman, Md. Hasanur, 2020; Smits et al., 1996; Thakuriah & Metaxatos, 2000 Hornstra & Maas, 2021; Converso et al., 2018). From the results of multinomial logistic regression, I find that individuals belonging to the treatment group have a significantly higher probability of being involved in occupation groups 2, 3, 4, and 5 compared to occupation group 1, as the relative risk ratios associated with the former occupation groups are greater than 1. The p-value associated with the relative risk ratios are significant at a 1% significance level. The results of the multinomial logit indicate that participants of 100WEEKs have a higher probability of being involved in entrepreneurial and agricultural occupations that could generate more income compared to occupation group 1, consisting of occupations where the workers get hired and paid daily. Such difference in occupation could be the possible explanation for the positive outcome in income. It must be mentioned that only 8 individuals in my sample of 722 research participants had no occupation (group 0), which made me refrain from using them in my analysis.

From the regression results conducted to address the issue of missing values, it can be seen that only the subdimension of assets shows a significant positive impact on the mean and median of income. The subdimension of assets is constructed with questions regarding ownership of productive assets such as sewing machines, livestock, and land ownership that can further generate income. Therefore one possible explanation for the increased income of the treatment group compared to the comparison group could be the increase in productive assets among the treatment group compared to the comparison group, as shown in Chapter 3.

From the p-values associated with the rest of the dimensions, as seen from the regression reported in Annex E, it cannot be concluded that the effect of other dimensions or subdimensions (except assets) on the mean and median of income is statistically different than 0. Thus, the results failed to direct us towards any other possible mechanism behind the increase in income. Nevertheless, it revalidates the argument that using income as a proxy for all the dimensions of poverty is not feasible as I see no statistically significant relationship between most of the dimensions and subdimensions of poverty and the mean and median of income. The Pearson's correlation test in Annex H confirms such interpretation as it shows the correlation between income and other subdimensions is statistically insignificant.

Lastly, one of the mechanisms behind the positive impact on the subdimension of income could be borrowed from behavioural economics. The poor, when exposed to the conditions of poverty over a longer period of time, display certain behaviours such as risk averseness and short-sightedness that can further trap them in poverty (Haushofer & Fehr, 2014). Providing cash to the poor has been shown to alter such poverty-inducing behaviour in a way that can help to break the cycle of poverty (Haushofer & Fehr, 2014). 100WEEKs provides the beneficiaries a cash transfer of 8 euros per week which could probably instigate positive behavioural change among them resulting in a positive impact on the mean and median of income.

Chapter 5: Limitations and Conclusion

This Chapter of the paper will discuss the trade-offs made while constructing the five dimensions, and the limitations of this research, followed by concluding remarks.

5.1 Trade-offs and Limitations

As the research utilized secondary data, I could not include certain subdimensions and variables while constructing the five dimensions proposed in the framework. Despite having questions regarding morbidity, and education in the monitoring and evaluation survey of 100WEEKs, I could not use the information for not having enough observations for the associated questions on morbidity and schooling. As I utilize methodologies such as factor analysis, which requires a large sample size (de Winter* et al., 2009), I had to exclude the data mentioned above. However, as the data I used for the research was collected during Covid-19, I reason that including the available data regarding morbidity, and education could misinform this research because the available question regarding morbidity could only capture whether the participants have felt sick in the last 7 days. No information was available regarding whether the sickness was related to Covid-19 or another disease. As the participants of 100WEEKs met each other during the training sessions every week, they could be more at risk of contracting Covid-19 compared to the comparison group. In contrast, training regarding nutrition and hygiene provided by 100WEEKs could potentially reduce other hygiene or malnutrition related diseases compared to the comparison group. In this situation, only capturing whether the research participants felt sick would not reflect the possible positive effect (reduction of other diseases related to hygiene and nutrition) or negative impact (increased chances of contracting Covid-19). In fact, there is a possibility that I observe the mean difference in the variable reporting morbidity between treatment and comparison group to be not significantly different than 0 despite having significant difference regarding the type of disease each group face, therefore misinforming my research results. Moreover, the education of children, which could be a crucial dimension of capacity, would not add much value to the research as, according to the country team in Rwanda, due to Covid-19, schools were closed. Therefore, no children could go to school.

Apart from data regarding morbidity and education, I could not include the subdimension of time usage as questions regarding time usage were not included in the monitoring and evaluation questionnaire of 100WEEKs. Previous research has found that when enrolled in interventions like multifaceted cash transfer programs, women have to invest time in the activities of the intervention in addition to the domestic work they already do. Therefore, women enrolled in an intervention often face time constraints leading to the absence of leisure (Baird et al., 2018). Leisure is an important component of living standard and would be a crucial indicator of the dimension of living standards (Soule, 1957). However, I could not capture the aspect of leisure and time constraint in my analysis due to insufficient information.

Moreover, due to the absence of observations, I could only use a binary variable indicating whether the participants own a house and land while constructing the subdimension of the asset. I could not capture information regarding the size of the land and house; as 100WEEK's team reports, it is usually hard for the beneficiaries to give numbers because of their low level of literacy. Due to not capturing the sizes of the lands and houses, I missed the information regarding 100WEEK's beneficiaries' expansion in the ownership of housing or land. For example, a participant could have $10m^2$ land before the intervention and $100m^2$ land by the end of the intervention. In both cases, the questions that only include binary land ownership choices will be answered positively. However, the improvement made in the amount of land owned will not be captured.

In addition to missing variables and subdimensions, in Chapter 4, I could only use 128 data points collected unevenly from different treatment groups to predict the variables related to income. The regression models used to predict the mean and median of income could explain 36% and 30% of the observed variation found in the 128 data points of income. Such a small sample size accompanied by a relatively poor fit of the regression models used to predict the mean and median of income makes me critical regarding the reliability of the predicted income data.

Moreover, I could not control the sampling procedure for the data collected for income. Therefore, I had to utilize financial diaries collected unevenly from different numbers of participants from different groups. Hence, hidden biases could affect the fitted variables of mean and median of income predicted for the entire sample. For example, the quality of training provided to different groups could differ depending on the quality of the trainer, which could further translate into differences in income-generating capacity across groups. Such differences in income generating capacity might indeed lead to differences in income earned by beneficiaries in different groups. In such circumstances, having more observations from certain groups and few observations from others could affect the accuracy of the predicted income for all the participants belonging to different groups. It could also be possible that only the participants who were financially doing well recorded their data in the financial diary. The participants who were not doing financially better did not use it overall, making us question the reliability of the predicted income data.

Lastly, while conducting propensity score matching, I constructed a counterfactual of the treatment group based on specific observed characteristics. Further, my results also passed sensitivity analysis, used to evaluate whether the results would still be significant if biases among the treatment and comparison groups are increased up to certain percentages (Gangl, 2004). However, I do not know to what extent the treatment and comparison groups differed from each other before participating in the intervention. Therefore, I am unable to conclude that there are no unobservable factors that could confound the results, as I did not have sufficient data to prove so.

5.2 Conclusion

The research shows that 100WEEK's intervention, a multifaceted cash transfer program, has a significant positive impact on the dimensions of health, living standard, income and assets, social capital, and capacity, which are the five dimensions of the five-dimensional framework proposed in this research. Further, the results point out that a multifaceted cash transfer program can efficiently address multiple constraints of poverty even during a global pandemic like Covid-19. However, the methodological constraints mentioned in the section on trade-offsand limitations make us hesitant regarding the generalizability of the results. Therefore, I propose future research to evaluate the proposed framework using a methodology like randomized control trial to ensure the generalizability of the framework. I want to emphasize that while re-conducting the research, ample data regarding the beneficiaries' income should be collected to obtain a credible perspective regarding the impact of a multifaceted cash transfer program on the subdimension of income. Additionally, it is noteworthy that the results in Chapter 3 indicated that 100WEEK's intervention negatively impacts the beneficiaries' psychological health. Hence, I find it necessary to suggest future research to particularly investigate the impact of multifaceted cash transfer programs on the psychological health of the beneficiaries. Such research is essential as it could indicate necessary amendments needed to eradicate the possible adverse effects of multifaceted cash transfer programs. Lastly, considering the caveats of propensity score matching discussed in the section on trade-offs and limitations, I want to propose that future assessments of interventions like multifaceted cash transfer programs should be done using methodologies that utilize both endline and baseline data to derive the impact. Examples of such methodologies are randomized control trial or difference in difference method. I am aware that organizations often target specific groups of individuals (i.e., poor women) as participants of their interventions; therefore, it is often not possible for them to randomize. In that case, I suggest selecting a group of potential beneficiaries and randomly assigning the group members into two groups; participants and prospective participants. Participants will first receive the intervention and can be the treatment groups, and prospective participants will receive the intervention in the future and can meanwhile act as a control group. In such a way, it will be possible to confirm the causal effect between the intervention and the outcome of interest for the selected beneficiaries, as selection bias would be tackled through randomization.

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ANNEX A: Questionnaire used to Construct the Dimensions

DIMENSIONS	QUESTIONS USED
HEALTH	
psychological health	In the last 7 days have you been feeling unhappy and depressed?
	In the last 7 days were you losing confidence in yourself?
	In the last 7 days were you thinking of yourself as a worthless person?
	In the last 7 days were you able to concentrate on whatever you were doing?
	In the last 7 days did you feel capable of making decision?
	In the last 7 days were you able to enjoy your normal day to-day activities?
	In the last 7 days did you lose a lot of sleep because of worries?
	In the last 7 days did you feel you were doing useful things?
	In the last 7 days did you that you couldn't overcome your difficulties?
	In the last 7 days did you feel capable of facing problems?
	In the last 7 days did you feel reasonably happy considering everything?
	In the last 7 days did you feel constantly under strain?
nutrition	In the last 7 days, did you / anyone else in your household older than 5 years of age eat any: meat, fish, milk or milk products, eggs, plantains or root vegetables, beans, other vegetables, fresh fruit, porridge
LIVING STANDARD	
material wellbeing	Does your household have electricity?
	What is the main source of lighting in the residence of the household?
	What is the main source of drinking water for members of the household?
	How long does it take you to go there, get water, and come back? (in minutes or hours)
	What kind of toilet facilities does your household use?
	What kind of toilet facilities does your household have?
	What types of fuel does the household mainly use for cooking?
	What is the main material of the floor of your household?
	Does any member of the household currently own a: hoe or shovel, rake and spade, pick, wheelbarrow, plough, cutlass, animal cart, machete
	Does any member of the household currently own: radio, table, chair, lantern or paraffin lamp, sewing machine, refrigerator, metal cooking pots, TV, landline telephone, computer
	Does any member of the household currently own: bicycle, three-wheel transport motorcycle, motorcycle, sofa/couch (cushion chair that fits more than one person), fan or ceiling fan, cupboard, electric stove, gas stove, car, truck
food security	In the past four weeks, did you worry that your household would not have enough food?
	If you had more money to spend, would you or any household member would want to eat different types of food?

	If you had more money to spend, would you or any household member eat a greater variety of foods?
	In the past four weeks, did it happen that your household had to eat some foods that you really did not want to eat, because you cannot afford to buy any other types of food?
	In the past four weeks, did your household have to eat a smaller meal than you felt you needed because there was not enough food?
	In the past four weeks, did you or any household member have to eat fewer meals in a day because there was not enough food?
	In the past four weeks, was there ever a time that you could not eat because you could not afford to buy food?
	In the past four weeks, did you or any household member go to sleep at night hungry because there was not enough food?
	In the past four weeks, did you or any household member go a whole day and night without eating anything because there was not enough food?
CAPACITIES	
financial buffer	How much do you save per day?
	Over the past month, how often did you or any member of the household…go without cash income
agency	Who usually makes decisions about making major household purchases?
	Who usually makes decisions about visits to family or relatives?
	Who usually decides how the money you earn will be used?
	Who usually decides how your (husband's/partner's) earnings will be used?
SOCIAL CAPITAL	Other people in the community sometimes ask you to take care of their children.
	You would be able to ask others in the community for advice or support if you needed it.
	Other people in the community often ask you for advice or support when they need it
	You are usually invited if there is a celebration in the community.
ASSETS	Which of the following animals does your household own? Cows, Goats, Bulls, Sheep, Rabbits, Guinea pigs, Pigs?
	Does the family own the house or rent the house?
	Does the family own their own plot of land?
	Does any member of the household currently own a: hoe or shovel, rake and spade, pick, wheelbarrow, plough, cutlass, machete, animal cart
	Does any member of the household currently own a: bicycle, three-wheel transport motorcycle, motorcycle, sofa/couch (cushion chair that fits more than one person), fan or ceiling fan, cupboard, electric stove, gas stove, car, truck
	Does the family own the house or rent the house?

ANNEX B: Results of Factor Analysis and KMO Tests

Table 1: Factor Analysis for Psychological health and corresponding KMO test

Factor	Eigenvalue	Difference	Proportion	Cumulative	Variable	kmo
					psychwel~2_4	0.8035
Factor1	2.49454	1.80525	0.8106	0.8106	psychwel~2_5	0.7064
Factor2	0.68929	0.13428	0.2240	1.0346	psychwel~2_6	0.6708
Factor3	0.55501	0.28278	0.1804	1.2149	psychwel~g_6	0.7080
Factor4	0.27224	0.15541	0.0885	1.3034	psychwel~2_1	0.6631
Factor5	0.11683	0.10226	0.0380	1.3414	psychwel~2_3	0.8184
Factor6	0.01457	0.10546	0.0047	1.3461	psychwel~g_4	0.7734
Factor7	-0.09089	0.03937	-0.0295	1.3166	psychwel~g_5	0.7962
Factor8	-0.13026	0.01668	-0.0423	1.2742	psychwel~2_2	0.8408
Factor9	-0.14694	0.03593	-0.0477	1.2265	psychwel~g_1	0.7704
Factor10	-0.18288	0.05338	-0.0594	1.1671	psychwel~g_2	0.5218
Factor11	-0.23626	0.04158	-0.0768	1.0903	psychwel~g_3	0.8310
Factor12	-0.27784	.	-0.0903	1.0000	Overall	0.7514

Table 2: Factor Analysis for Assets of Material wellbeing and corresponding KMO test

Factor	Eigenvalue	Difference	Proportion	Cumulative	Variable	kmo
					shoescloth~1	0.5322
Factor1	1.21377	0.21701	0.6277	0.6277	shoescloth~2	0.5074
Factor2	0.99676	0.53336	0.5155	1.1431	bedsnets_1	0.5415
Factor3	0.46339	0.42297	0.2396	1.3828	bedsnets_2	0.5258
Factor4	0.04042	0.02735	0.0209	1.4037	assetsmat~_7	0.6862
Factor5	0.01307	0.10615	0.0068	1.4104	assetsmat~_8	0.6073
Factor6	-0.09308	0.11523	-0.0481	1.3623	assetsmat~_9	0.6395
Factor7	-0.20831	0.01501	-0.1077	1.2546	assetsmat~10	0.3720
Factor8	-0.22332	0.04565	-0.1155	1.1391	assetsmat~13	0.5758
Factor9	-0.26897	.	-0.1391	1.0000	Overall	0.5568

Table 3: Factor Analysis for the subdimension of Agency and corresponding KMO test

Factor	Eigenvalue	Difference	Proportion	Cumulative	Variable	kmo
Factor1	2.90214	2.83729	1.0519	1.0519	hhpurchases	0.7937
Factor2	0.06485	0.16235	0.0235	1.0754	decisionfam	0.8247
Factor3	-0.09749	0.01307	-0.0353	1.0401	hermoney	0.8485
Factor4	-0.11056	.	-0.0401	1.0000	hismoney	0.8228
					Overall	0.8207

Table 4: Factor Analysis for the dimension of Social Capital and corresponding KMO test

Factor	Eigenvalue	Difference	Proportion	Cumulative	Variable	kmo
					socialsupp~1	0.8568
Factor1	1.39674	1.40651	1.2887	1.2887	socialsupp~2	0.6575
Factor2	-0.00976	0.09025	-0.0090	1.2797	socialsupp~3	0.6375
Factor3	-0.10002	0.10314	-0.0923	1.1874	socialsupp~4	0.7629
Factor4	-0.20315	.	-0.1874	1.0000	Overall	0.6779

Table 5: Factor Analysis for the subdimension of asset and corresponding KMO test

Factor	Eigenvalue	Difference	Proportion	Cumulative	Variable	kmo
					assetsmat~_1	0.6090
Factor1	1.15388	0.73125	0.9374	0.9374	**assetsmat~_2**	0.6832
Factor2	0.42262	0.04504	0.3433	1.2807	**assetsmat~_3**	0.6576
Factor3	0.37758	0.26183	0.3067	1.5874	**assetsmat~_4**	0.5918
Factor4	0.11575	0.03166	0.0940	1.6814	**assetsmat~_6**	0.5055
Factor5	0.08409	0.05130	0.0683	1.7498	**assetsmat~11**	0.6690
Factor6	0.03279	0.04736	0.0266	1.7764	**assetsmat~19**	0.5033
Factor7	-0.01457	0.09280	-0.0118	1.7646	**assetsm~3_14**	0.7046
Factor8	-0.10737	0.03951	-0.0872	1.6773	**assetsm~3_16**	0.5035
Factor9	-0.14687	0.05789	-0.1193	1.5580	**rentownhouse**	0.6474
Factor10	-0.20477	0.02211	-0.1663	1.3917	**ownsland**	0.6718
Factor11	-0.22687	0.02841	-0.1843	1.2074	**TLU_score**	0.6020
Factor12	-0.25528	.	-0.2074	1.0000	**Overall**	0.6288

ANNEX C: Rosenbaum Sensitivity Analysis for Chapter 3

Capacity

Rosenbaum bounds for delta5 (N = 320 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	.772721	.772721	.684997	.877432
1.5	0	0	.642127	.961831	.562441	1.08847
2	5.8e-14	0	.555729	1.09604	.433737	1.19691
2.5	5.0e-10	0	.469041	1.17673	.297564	1.28425
3	1.7e-07	0	.358085	1.24139	.216868	1.37004

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

Social Capital

Rosenbaum bounds for delta4 (N = 320 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	.084245	.084245	.084245	.084245
1.5	9.8e-12	0	.084245	.084245	.084245	.16849
2	2.2e-07	0	.084245	.16849	-4.8e-07	.16849
2.5	.000061	0	-4.8e-07	.16849	-4.8e-07	.16849
3	.001919	0	-4.8e-07	.16849	-4.8e-07	.982632

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

Assets

Rosenbaum bounds for delta3 (N = 320 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	1.22834	1.22834	1.10766	1.35162
1.5	0	0	1.03584	1.41844	.908984	1.54622
2	0	0	.898695	1.55582	.765156	1.67963
2.5	8.9e-16	0	.791221	1.65365	.653262	1.78716
3	1.1e-12	0	.70833	1.73437	.564157	1.86919

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

Living standard

Rosenbaum bounds for delta2 (N = 320 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	1.29407	1.29407	1.18661	1.40835
1.5	0	0	1.1218	1.47411	1.01164	1.59508
2	0	0	1.00279	1.60372	.888155	1.72571
2.5	0	0	.91254	1.69991	.797786	1.82642
3	3.3e-16	0	.839748	1.77779	.721195	1.91012

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

Health

Rosenbaum bounds for delta2 (N = 320 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	1.4e-13	1.4e-13	.558623	.558623	.416381	.702256
1.5	9.0e-06	0	.328931	.786224	.179911	.933754
2	.011758	0	.167474	.945134	.025123	1.09518
2.5	.232935	0	.055722	1.06212	-.091885	1.22125
3	.697762	0	-.035794	1.15939	-.181822	1.32829

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

ANNEX D: Sensitivity Analysis and Multiple Hypothesis Testing for Chapter 4

Results for Rosenbaum Sensitivity Analysis

Table 1:Mean Income

Rosenbaum bounds for delta7 (N = 320 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	5.9e-07	5.9e-07	.322862	.322862	.192822	.455201
1.5	.036379	2.2e-16	.11797	.531037	-.010628	.667246
2	.628493	0	-.020757	.678266	-.153668	.823005
2.5	.975945	0	-.126638	.79403	-.265638	.950023
3	.999582	0	-.211559	.888353	-.357958	1.05436

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

Table 2: Median Income

Rosenbaum bounds for delta8 (N = 320 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	5.9e-07	5.9e-07	.322862	.322862	.192822	.455201
1.2	.000266	1.5e-10	.229183	.415669	.101268	.5485
1.4	.010523	2.2e-14	.152718	.495746	.024099	.630742
1.6	.09399	0	.088598	.562989	-.041342	.702704
1.8	.327134	0	.02956	.623818	-.099758	.765204
2	.628493	0	-.020757	.678266	-.153668	.823005

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

Table 3: Results of Multiple Hypthesis testing

p value	Sharpened q value
.001805	0.002
.001309	0.002

ANNEX E: Regression from Section 4.3a

Table 1: Regression Mean Income

	(1) mean_revenue	(2) mean_revenue	(3) lnmeanincome	(4) lnmeanincome
z_health	-9560.9		-0.117	
	(-0.22)		(-1.08)	
z_living_standard	-48117.8		-0.0945	
	(-0.98)		(-0.77)	
z_asset	63690.7	52013.8	0.232^{**}	0.171^{*}
	(1.95)	(1.53)	(2.82)	(2.06)
z_capacity	-3950.9		0.00790	
	(-0.09)		(0.07)	
z_socialcapital	31633.8	23087.4	0.112	0.0569
	(0.56)	(0.40)	(0.79)	(0.40)
0.occupation	0	0	0	0
	(.)	(.)	(.)	(.)
2.occupation	-270411.6	-324948.2	-0.243	-0.488
	(-1.69)	(-1.96)	(-0.60)	(-1.21)
3.occupation	-174115.3	-225191.6	-0.474	-0.696
	(-1.06)	(-1.32)	(-1.15)	(-1.67)
4.occupation	-293090.8	-327939.2	-0.488	-0.599
	(-1.73)	(-1.89)	(-1.15)	(-1.41)
5.occupation	-294180.0	-373323.0	-0.408	-0.743
	(-1.14)	(-1.40)	(-0.63)	(-1.14)
Schoolatt	35849.9	34884.5	0.0864	0.0826
	(0.81)	(0.79)	(0.78)	(0.76)
howmanyhhm_1	24203.3	24435.5	0.0376	0.0403
	(0.68)	(0.68)	(0.42)	(0.46)
age_1	-3389.9	-2920.7	-0.00693	-0.00799
	(-0.32)	(-0.27)	(-0.26)	(-0.30)
Partner	-13960.0	54718.4	0.0215	0.220
	(-0.10)	(0.29)	(0.06)	(0.47)
Schoolagedchildren	-12757.4	-6768.0	0.0160	0.0635
	(-0.23)		(0.11)	
Endate	-0.00000460	-0.00000319	$8.78e-11^{***}$	$9.67e-11^{***}$
	(-0.47)	(-0.31)	(3.56)	(3.90)
location	-107161.0^{*}	-107060.8^{*}	-0.353^{**}	-0.356^{**}
	(-2.05)	(-1.99)	(-2.69)	(-2.70)

z_psychological_health		-62274.0		-0.313*
		(-1.05)		(-2.16)
z_nutrition		33125.7		0.0599
		(0.63)		(0.47)
z_materialwellbeing		-42809.3		-0.157
		(-1.13)		(-1.69)
z_foodsecurity		-6780.4		0.152
		(-0.11)		(1.05)
z_financialcoping		-8767.8		-0.0351
		(-0.27)		(-0.44)
z_agency		-26346.9		-0.0146
		(-0.31)		(-0.07)
_cons	93326528.9	64801490.9	-1762.7***	-1942.4***
	(0.47)	(0.32)	(-3.54)	(-3.88)
N	128	128	128	128
R^2	0.108	0.125	0.256	0.309

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Regression Median Income

	(1) median_revenue	(2) median_revenue	(3) lnmedianincome	(4) lnmedianincomehat
z_health	-11424.2		-0.0808	
	(-0.44)		(-0.89)	
z_living_standard	-11288.6		-0.0487	
	(-0.39)		(-0.48)	
z_asset	30308.0	28867.5	0.137*	
	(1.55)	(1.42)	(2.00)	
z_capacity	20418.0		0.0636	
	(0.79)		(0.70)	
z_socialcapital	20623.1	19795.4	0.0480	
	(0.60)	(0.57)	(0.40)	
schoolatt	33645.7	33936.7	0.0856	0.0638***
	(1.26)	(1.26)	(0.92)	(5.62)
howmanyhhm_1	-9404.8	-9806.4	0.0122	0.00430
	(-0.44)	(-0.45)	(0.16)	(0.47)
age_1	-3700.1	-3735.9	-0.0104	-0.0124***
	(-0.58)	(-0.57)	(-0.46)	(-5.15)
partner	-45653.7	-60489.6	-0.0404	0.0925***
	(-0.54)	(-0.52)	(-0.14)	(5.35)
Schoolagedchildr	1414.2	2044.8	0.0710	0.0924***

en				
	(0.04)	(0.06)	(0.61)	(6.51)
endate	0.00000114	0.00000114	8.75e-11***	9.86e-11***
	(0.20)	(0.19)	(4.36)	(63.45)
location	-48714.4	-48072.0	-0.365***	-0.392***
	(-1.63)	(-1.57)	(-3.48)	(-53.40)
z_psychological_ health		-17436.6		
		(-0.50)		
z_nutrition		-3943.4		
		(-0.12)		
z_materialwellbei ng		-8285.5		
		(-0.37)		
z_foodsecurity		-3120.8		
		(-0.09)		
z_financialcoping		11998.8		
		(0.61)		
z_agency		25758.4		
		(0.51)		
T				0.535***
				(27.09)
_cons	-22820597.7	-22825678.5	-1757.0***	-1982.1***
	(-0.20)	(-0.19)	(-4.33)	(-63.11)
N	128	128	128	722
R^2	0.081	0.083	0.273	0.925

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: VIF Results

Table 3a: VIF test for regression of ln_mean income

Variable	VIF	1/VIF
z_psycholo~h	1.23	0.815360
z_nutrition	1.08	0.925318
z_material~g	1.24	0.807024
z_foodsecu~y	1.19	0.839064
z_financia~g	1.12	0.895956
z_agency	2.30	0.434578
z_asset	1.19	0.839460
z_socialca~l	1.11	0.903739
occupation		

Table 3b: VIF test for regression of ln_median_income

Variable	VIF	1/VIF
z_psycholo~h	1.23	0.815360
z_nutrition	1.08	0.925318
z_material~g	1.24	0.807024
z_foodsecu~y	1.19	0.839064
z_financia~g	1.12	0.895956
z_agency	2.30	0.434578
z_asset	1.19	0.839460
z_socialca~l	1.11	0.903739
occupation		

2	5.42	0.184463	**2**	5.42	0.184463
3	5.23	0.191253	**3**	5.23	0.191253
4	3.35	0.298168	**4**	3.35	0.298168
5	1.75	0.571520	**5**	1.75	0.571520
schoolatt	1.33	0.751951	**schoolatt**	1.33	0.751951
howmanyhhm_1	2.25	0.444518	**howmanyhhm_1**	2.25	0.444518
age_1	2.31	0.432849	**age_1**	2.31	0.432849
partner	2.26	0.442122	**Partner**	2.26	0.442122
schoolaged~n	2.35	0.426085	**schoolaged~n**	2.35	0.426085
endate	1.24	0.806088	**Endate**	1.24	0.806088
location	1.32	0.757530	**location**	1.32	0.757530
Mean VIF	2.07		**Mean VIF**	2.07	

ANNEX F: Multinomial Logistic Regression

Table 1: Occupation per Occupation Group

Occupation group	Occupation	Occupation type
1	a. Day labourer b.Day labourer house builder/mason d. Day labourer transport	Occupations that are paid on a daily basis
2	a. Shopkeeper b. Street vendor c. Firewood seller	Occupations that are slightly entrepreneurial
3	a. Farmer, grows crops on own land b. Farmer, has livestock on own land	Agricultural occupation on own land
4	a. Market Vendor b. Making and selling beer (or other alcoholic beverages) c. Restaurant /making and selling food d. Making/ repairing clothes e. Handcraft maker f. Local tailor	Occupations that are entrepreneurial
5	a. Farmer, grows crops on rented land b. Farmer has livestock on rented land	Agricultural occupation on rented land

Table 2: Results of Multinomial Logistic Regression

1	(base outcome)					
2						
T	3.378071	.74526	4.53	0.000***	1.917388	4.838754
Schoolatt	.2931835	.1897211	1.55	0.122	-.0786631	.6650301
howmanyhhm_1	-.1868201	.1489092	-1.25	0.210	-.4786767	.1050365
age_1	.0554313	.0403237	1.37	0.169	-.0236016	.1344642
partner	-.1220732	.2450885	-0.50	0.618	-.6024379	.3582914
schoolagedchildren	.3944857	.2440378	1.62	0.106	-.0838196	.872791
childmortality	.138803	.5164839	0.27	0.788	-.8734869	1.151093
endate	-1.75e-10	3.10e-11	-5.63	0.000	-2.36e-10	-1.14e-10
location	-.392405	.112063	-3.50	0.000	-.6120445	-.1727656
_cons	3528.803	627.2729	5.63	0.000	2299.37	4758.235
3						
T	3.761415	.7515907	5.00	0.000***	2.288324	5.234505
schoolatt	.0315835	.2084527	0.15	0.880	-.3769763	.4401434
howmanyhhm_1	-.2684996	.1604419	-1.67	0.094	-.5829599	.0459607
age_1	.1368486	.0427857	3.20	0.001	.0529901	.2207071
partner	-.6640293	.3310685	-2.01	0.045	-1.312912	-.0151469
schoolagedchildren	.1482298	.2551099	0.58	0.561	-.3517765	.648236
childmortality	.1635766	.5400634	0.30	0.762	-.8949283	1.222081

endate	-6.07e-11	3.12e-11	-1.94	0.052	-1.22e-10	4.79e-13
location	-.0713053	.1202124	-0.59	0.553	-.3069172	.1643066
_cons	1222.762	630.2062	1.94	0.052	-12.41917	2457.944
4						
T	3.667128	.7682537	4.77	0.000***	2.161378	5.172878
schoolatt	.1923806	.2211326	0.87	0.384	-.2410313	.6257925
howmanyhhm_1	-.1229434	.1787429	-0.69	0.492	-.473273	.2273862
age_1	.0518627	.0475435	1.09	0.275	-.0413208	.1450462
partner	-.4242195	.3555471	-1.19	0.233	-1.121079	.2726401
schoolagedchildren	.2413653	.2830161	0.85	0.394	-.313336	.7960666
childmortality	.1386091	.5895245	0.24	0.814	-1.016838	1.294056
endate	-9.49e-11	3.45e-11	-2.75	0.006	-1.63e-10	-2.72e-11
location	-.6031626	.163798	-3.68	0.000	-.9242007	-.2821245
_cons	1916.967	697.4953	2.75	0.006	549.9008	3284.032
5						
T	1.781664	.7790159	2.29	0.022**	.2548212	3.308507
schoolatt	.2342749	.2011516	1.16	0.244	-.159975	.6285247
howmanyhhm_1	-.0552122	.1582632	-0.35	0.727	-.3654024	.2549779
age_1	.0952372	.0430786	2.21	0.027	.0108047	.1796697
partner	-.8320064	.4008906	-2.08	0.038	-1.617738	-.0462751
schoolagedchildren	-.2024696	.2611777	-0.78	0.438	-.7143686	.3094293
childmortality	-.819674	.5096313	-1.61	0.108	-1.818533	.1791851
endate	-4.16e-11	3.18e-11	-1.31	0.191	-1.04e-10	2.07e-11
location	.0001968	.1175213	0.00	0.999	-.2301407	.2305344
_cons	840.3516	642.4991	1.31	0.191	-418.9235	2099.627

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

ANNEX G: Pearson’s Correlation Test

Table 1: Pearson’s Correlation Test for mean_income

mean_income	1.0000						
z_health	-0.0435	1.0000					
	0.6256						
z_living_s~d	-0.0098	0.1503	1.0000				
	0.9123	0.0001					
z_asset	0.1843	0.1164	0.4550	1.0000			
	0.0373**	0.0017	0.0000				
z_socialca~l	0.0352	0.0544	0.0625	0.0978	1.0000		
	0.6929	0.1439	0.0932	0.0086			
z_capacity	-0.0091	0.2086	0.3145	0.1607	-0.0284	1.0000	
	0.9188	0.0000	0.0000	0.0000	0.4462		
schoolatt	0.0390	0.0660	0.0918	-0.0882	0.0222	0.0263	1.0000
	0.6618	0.0766	0.0136	0.0177	0.5514	0.4812	
howmanyhhm_1	0.0556	0.0564	0.0627	0.1487	-0.0085	-0.0067	-0.2941
	0.5329	0.1302	0.0921	0.0001	0.8190	0.8580	0.0000
age_1	-0.0104	0.0288	0.1079	0.1708	0.0331	0.0331	-0.3698
	0.9073	0.4395	0.0037	0.0000	0.3751	0.3749	0.0000
partner	-0.0209	0.0790	-0.0569	-0.1108	-0.0452	0.3910	0.0368
	0.8150	0.0338	0.1266	0.0029	0.2254	0.0000	0.3229
schoolaged~n	0.0001	0.0529	0.0345	0.1043	-0.0042	0.0689	-0.3778
	0.9989	0.1558	0.3540	0.0050	0.9110	0.0644	0.0000
endate	-0.0070	-0.1426	-0.1003	-0.1502	0.0292	-0.0954	0.0865
	0.9377	0.0001	0.0070	0.0001	0.4335	0.0103	0.0201
location	-0.1564	-0.0154	-0.1480	-0.1905	-0.0831	-0.0066	0.0435
	0.0779	0.6799	0.0001	0.0000	0.0255	0.8593	0.2427

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.

Table 2: Pearson’s Correlation Test for median_income

median_inc~e	1.0000	
z_health	-0.0766	1.0000
	0.3899	

z_living_s~d	0.0449	0.1503	1.0000				
	0.6151	0.0001					
z_asset	0.1149	0.1164	0.4550	1.0000			
	0.1966	0.0017	0.0000				
z_socialca~l	0.0273	0.0544	0.0625	0.0978	1.0000		
	0.7597	0.1439	0.0932	0.0086			
z_capacity	0.0476	0.2086	0.3145	0.1607	-0.0284	1.0000	
	0.5939	0.0000	0.0000	0.0000	0.4462		
Schoolatt	0.1545	0.0660	0.0918	-0.0882	0.0222	0.0263	1.0000
	0.0815	0.0766	0.0136	0.0177	0.5514	0.4812	
howmanyhhm_1	-0.0708	0.0564	0.0627	0.1487	-0.0085	-0.0067	-0.2941
	0.4268	0.1302	0.0921	0.0001	0.8190	0.8580	0.0000
age_1	-0.1321	0.0288	0.1079	0.1708	0.0331	0.0331	-0.3698
	0.1372	0.4395	0.0037	0.0000	0.3751	0.3749	0.0000
Partner	-0.0106	0.0790	-0.0569	-0.1108	-0.0452	0.3910	0.0368
	0.9058	0.0338	0.1266	0.0029	0.2254	0.0000	0.3229
schoolaged~n	-0.0797	0.0529	0.0345	0.1043	-0.0042	0.0689	-0.3778
	0.3714	0.1558	0.3540	0.0050	0.9110	0.0644	0.0000
Endate	0.0132	-0.1426	-0.1003	-0.1502	0.0292	-0.0954	0.0865
	0.8829	0.0001	0.0070	0.0001	0.4335	0.0103	0.0201
Location	-0.1468	-0.0154	-0.1480	-0.1905	-0.0831	-0.0066	0.0435
	0.0982	0.6799	0.0001	0.0000	0.0255	0.8593	0.2427

*Significant at 10%; **Significant at 5%; ***Significant at 1% level.