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Beyond the Surface: An Empirical Analysis of Multidimensional Child Poverty in Zambia

by

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Abstract: Zambia has one of the highest levels of child poverty in Sub-Saharan Africa. However, child poverty remains an understudied area and the determinants thereof are not well understood. This dissertation aims to bridge this gap by identifying the determinants of multidimensional child poverty through the estimation of a probit model using LCMS 2015 data. The findings of this study highlight several key determinants that significantly impact the probability of a child experiencing poverty in Zambia. Specifically, young male children have a higher likelihood of experiencing child poverty. Furthermore, children living in a household headed by a young or old individual engaged in self-employment with a low educational level are more prone to child poverty. The results also show that residing in rural areas and having a mother with limited education contribute significantly to increased child poverty. Additionally, this dissertation adds to the literature by examining the causal effect of rural-to-urban migration on child poverty in the short term. The Propensity Score Matching analysis reveals that rural-to-urban migration significantly decreases the probability of a child being poor by over 20 percentage points on average. This dissertation emphasizes the need for well-targeted policies fighting multidimensional child poverty in rural Zambia. Even though rural-to-urban migration is one potential solution to escape poverty, it increases the pressure on urban infrastructures. Therefore, increased investments in the local development of rural areas are needed.

Keywords: *Multidimensional Child Poverty, Determinants, Rural-to-Urban Migration, Zambia, Sub-Saharan Africa*

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1. Introduction

In order to address the pressing issue of global poverty, urgent action is required to reduce both its monetary and multidimensional aspects. Thus, the Sustainable Development Goals (SDGs), specifically Target 1.1 and 1.2, were introduced in 2015 with the ambitious aim of eradicating extreme poverty by 2030. Extreme poverty is currently defined as living below the threshold of 1.25 US dollars per day, and the SDGs also seek to reduce the overall proportion of individuals, including men, women, and children, experiencing poverty in all its dimensions (United Nations, 2023). The necessity of poverty reduction has long been recognized, as exemplified by a statement in a 1990 World Bank report that "poverty alleviation is what economic development is all about" (World Bank, 1990, p.57).

From a global perspective, Sub-Saharan Africa is the world's region with the highest share of people living in poverty with less than 2.15 US dollars per day (Hasell, Roser, Ortiz Ospina & Arriagada, 2022). Zambia is amongst the countries that show the highest incidences of poverty. Even though the country has experienced a period of economic growth since the millennium turn, poverty levels have remained high. In 2015, over 61% of the population have lived below a level of 2.15 US dollars per day in 2017 PPP (World Bank, 2023). Similarly, the share of children of the total population is high, with over 53% being younger than 18 years of age (UNICEF, n.d.). The overall high level of poverty and share of children suggests that many children suffer from poverty in monetary and multidimensional terms. To progress towards the SDGs and adequately fight child poverty in Zambia, it is crucial to have a deep understanding of the factors affecting child poverty and any causal mechanism that might exist. The fundamental research questions this thesis seeks to address are: What are the determinants of multidimensional child poverty in Zambia? Does rural-to-urban migration affect child poverty?

The child poverty literature acknowledges the need for a differential analysis of child poverty compared to overall poverty (White, Leavy & Masters, 2003). Generally, there is a plethora of research on child poverty in Sub-Saharan Africa (Ferrone & De Milliano, 2018; Lekobane & Roelen, 2020). Even though most studies include similar variables when ascertaining the determinants of child poverty, such as child and household characteristics, no consensus is reached on the mechanism that drive child poverty. Additionally, the specific characteristics of child poverty are country-specific and significantly depend on the context they are studied. For this reason, it is imperative to take a case study approach in order to understand country-specific determinants of child poverty. This study focusses on understanding the determinants of child poverty in Zambia. Even though Zambia has a high level of child poverty, it has been relatively understudied. In a multidimensional framework, the only study that analyzes child poverty was conducted by the Ministry of National Development Planning (2018). Whereas the study extensively analyzes the descriptive aspects of child poverty such as in which dimensions children at different ages are deprived, it falls short on analyzing the determinants of child poverty. As the determinants vary depending on the context, a comprehensive analysis of the determinants of multidimensional child poverty in Zambia is needed to optimally target the most vulnerable children in fighting child poverty.

The literature dealing with the determinants of child poverty has been restricted to estimating correlations between certain determinants and child poverty. An analysis of causal mechanisms is needed to improve our understanding of the determinants. As residing in rural areas is one of the strongest determinants of child poverty (De Milliano & Plavgo, 2018; Lekobane & Roelen, 2020), one such causal mechanism is the effect of rural-to-urban migration on child poverty. However, the topic of rural-to-urban migration has been relatively understudied in Sub-Saharan Africa (De Brauw, Mueller & Lee, 2014) and the consequences on child poverty are unknown, as previous research has mostly focused on the household, family, or employment seeker as the unit of analysis. Even though these studies find a positive welfare effect of rural-to-urban migration (Mukhtar, Zhong, Tian, Razzaq, Naseer & Hina, 2018; Nguyen, Raabe & Grote, 2015), more investigation is needed because the increasing pressure on urban infrastructures may lead to urban poverty (Awumbila, Owusu & Teye, 2014) and the risk of settling in informal settlements is associated with low living standards (Fonta et al., 2020; Islam & Azad, 2007; Ullah, 2004). These risks prevail especially in a multidimensional sense.

This dissertation contributes to the literature in several ways. Firstly, it adds to the child poverty literature in Zambia with a detailed and comprehensive discussion of the determinants of child poverty. Secondly, the literature has been restricted to estimating correlations between certain determinants and child poverty. This dissertation goes beyond correlations by estimating the causal effect of rural-to-urban migration on child poverty in Zambia. This is a significant contribution, as publications on the causal effects of rural-to-urban migration are limited. To my best knowledge, no study has yet researched the impact of rural-to-urban migration on child poverty. Existing studies have focused on the effects of rural-to-urban migration on the household, family, or the employment seeker as the unit of analysis. However, a differential analysis of the child is needed, as children differ from adults regarding their rights and development. This will be further elaborated on in section 3.1.2.

The following analysis is based on data from the LCMS VII 2015 in Zambia. The estimation of a multidimensional child poverty index is at the heart of the analysis, classifying a child as poor if it is deprived of access to at least three out of six dimensions. I will elaborate on the determinants of child poverty in Zambia by applying a probit model, including an estimation of the marginal effects. Whereas this is rather common in the child poverty literature, it has not yet been examined in the context of Zambia. When estimating the causal effect of rural-to-urban migration on child poverty, it is crucial to account for the self-selection of rural-to-urban migrants. Therefore, a Propensity Score Matching (PSM) analysis is performed. The results are obtained using two different matching techniques, stratification, and weighting.

The results reveal that especially young, male children residing in rural areas, with a relatively young or old household head, who has low levels of education and is self-employed are at risk to suffer from multidimensional poverty. Additionally, the educational level of the mother, household size, and number of children in the household were found to be significant determinants of child poverty in Zambia.

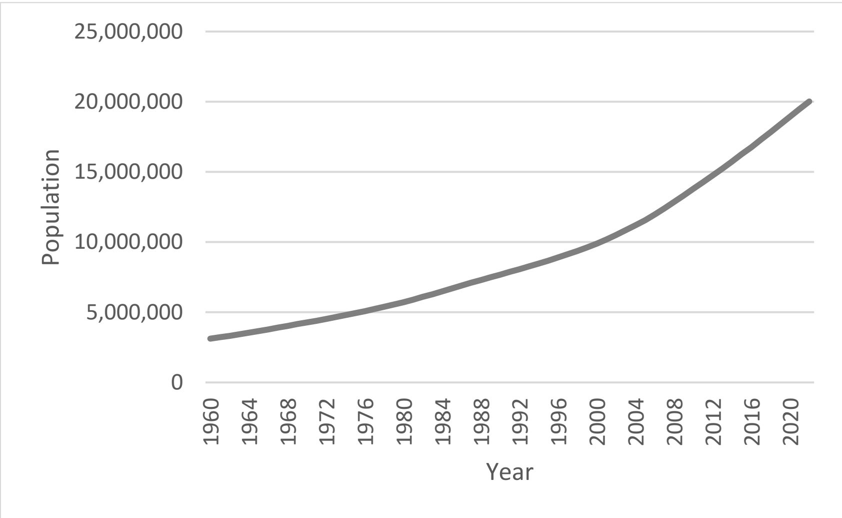
Residing in rural areas stands out as one main determinant of child poverty, warranting a further analysis of the effect of rural-to-urban migration. The PSM estimations revealed that rural-to-urban migration significantly reduces the probability of children being multidimensionally poor by an estimated 20 percentage points on average, which are likely to be slightly underestimated. This confirms the main hypothesis of this dissertation.

This dissertation is structured as follows. After providing the research context in section 2, the theory and previous research is presented in section 3. Section 4 deals with the data used and section 5 covers the methodology applied. The estimation results are presented in section 6. Before concluding in section 8, the findings are discussed in the light of previous research in section 7.

2. Context

The purpose of this section is to provide some country-specific context to Zambia. Zambia is a landlocked country located in South Africa. It borders Angola, Botswana, the Democratic Republic of the Congo, Malawi, Mozambique, Namibia, and Tanzania. The country gained its independence from Britain in 1964. Since the mid-20th century, Zambia's population has grown exponentially, reaching about 20 million inhabitants in 2022 (*figure 1*). The population is very young, characterized by a high share of children with over 50% (UNICEF, n.d.).

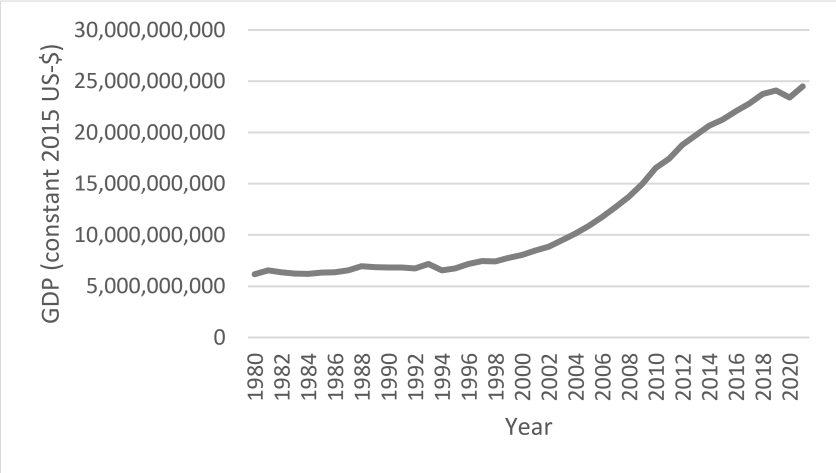
Figure 1: Population



Source: World Bank, 2023

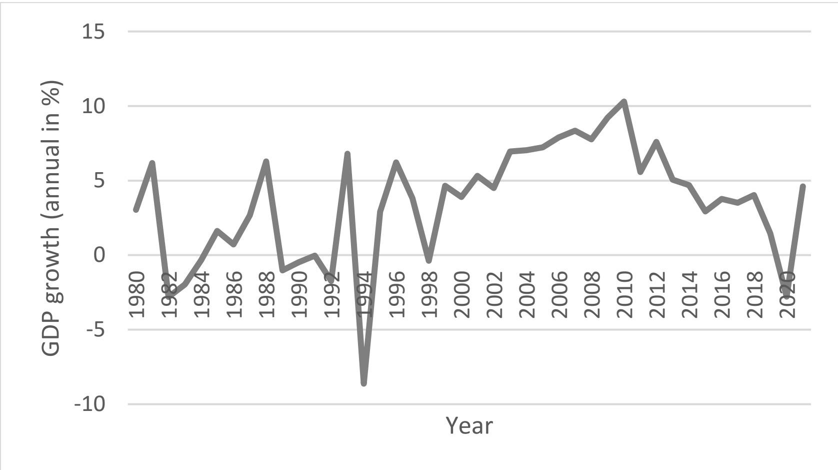
The country has experienced relatively stable economic growth since the turn of the century. *Figure 2* presents the GDP, measured in constant 2015 US dollars, which increased from 6 billion US dollars in the 1990s to almost 25 billion US dollars in 2021. *Figure 3* shows that since the turn of the century, the annual GDP growth rate has constantly remained positive, except for 2020, with the decline most probably related to Covid-19.

Figure 2: GDP in Constant 2015 US Dollars



Source: World Bank, 2023

Figure 3: GDP Growth (Annual in %)



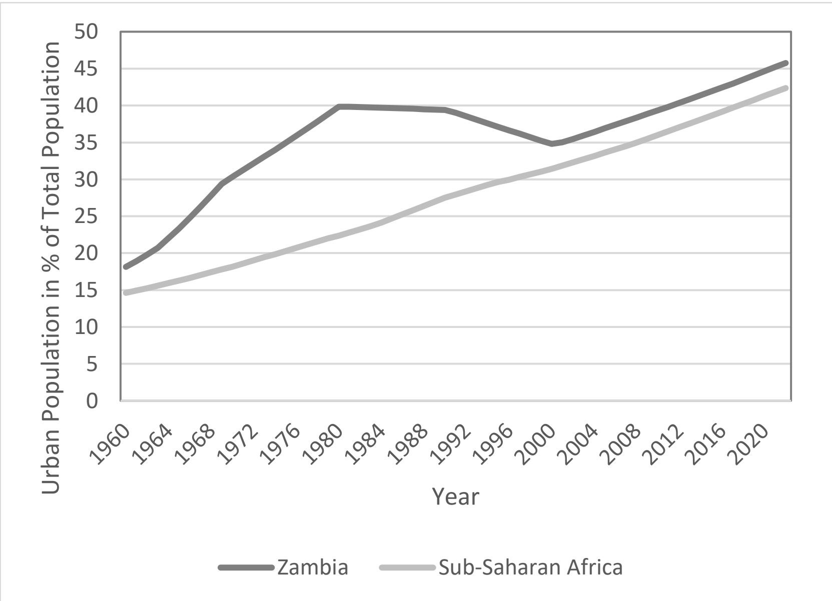
Source: World Bank, 2023

However, the economic development does not seem to have reached everyone. Despite its development, poverty and child poverty have remained at high levels. As mentioned previously, it is estimated that in 2015 over 61% of the population lived below a level of 2.15 US dollars per day in 2017 PPP (World Bank, 2023). For the same year, the Ministry of National Development Planning (2018) estimates 60% of all children poor in monetary terms. From a multidimensional poverty perspective, about 80% of children are deprived of access to at least one basic good, which is essential to them.

Some programs implemented in the last years to fight poverty are regular social cash transfers, a national food and nutrition strategic plan, and a youth empowerment and employment program. About 20% of the Zambian population is registered to receive regular social cash transfers. Regular social cash transfers have positively contributed to fighting poverty. It increased the productivity of poor households' land usage, which led to increases in food production, and material well-being of children (World Bank, 2021). The national food and nutrition plan aims to improve children's living standards. Above all, the plan aims to expand interventions to promote the first 1000 most critical days of life. Improving nutrition conditions from the start of pregnancy until a child is two years of age is crucial for long-term health outcomes (National Food and Nutrition Commission of Zambia, 2012). The youth empowerment and employment program acknowledged the issues of structural youth unemployment in the country and aims at providing an employment-friendly environment for young men and women. One factor supporting the youth is the acquisition of employable skills, which are expected to facilitate access to the formal labor market (Ministry of Youth and Sport, 2015). Despite the efforts, poverty levels remain high. In fact, due to the fast-growing population, children might be more at risk of suffering from poverty relative to the overall population. Therefore, the need for further policies targeting child poverty persists.

Shifting the focus to rural-to-urban migration, *figure 4* displays that Zambia is characterized by a relatively high level of urbanization above the Sub-Saharan average. In 2021, about 45% of the Zambian population lived in urban areas.

Figure 4: Urban Population in % of Total Population



Source: World Bank, 2023

Urban population growth and migration are two major factors contributing to the increasing urbanization rate. As Crankshaw and Borel-Saladin (2019) argue, net migration is the main cause of urbanization growth in Zambia. Migration flows are thereby connected to the previously presented economic development in Zambia. Whereas the decline in urbanization during the last two decades of the 20th century corresponds to economic stagnation, the rise in the urbanization rate is mainly caused by the observed economic development since the turn of the century. Rapid economic development created employment opportunities, which led to increases in rural-to-urban migration.

Alongside economic development, there has been a structural change in sectoral employment. The share of people working in agriculture has decreased from about 70% in the 1990s to 59% in 2021. Over the same period, the share of people working in services has increased from about 20% to 33%. Meanwhile, the share of industry workers has remained relatively constant, presenting only a small increase from about 7% to 9%. Even though the trend suggests significant declines in the share of agriculture employment, most of the Zambian population is still working in agriculture today (World Bank, 2023). Besides a significant share of those working in the informal sector, they face precarious working conditions and limited social security (International Labour Organization, n.d).

3. Theory and Previous Research

The literature review is divided into three parts. The first part deals with the economic theory of measuring poverty and child poverty more specifically, contrasting the two perspectives of the welfarist and non-welfarist approaches. The relevant literature about the determinants of child poverty is reviewed in the second part. The last part of the literature review focuses on the causal effects of rural-to-urban migration on child poverty.

3.1. Economic Theory

3.1.1. The Welfarist and Non-Welfarist Approaches to Measuring Poverty

The two main problems in measuring poverty are identification and aggregation, which deal with questions such as how to best assess economic well-being and how to aggregate this information into a single measure (Ravallion, 1992). There exist two approaches to measuring poverty, which can be classified into the welfarist and non-welfarist approaches. These have important conceptual differences (Ravallion, 1998). The welfarist approach bases well-being on individual utilities and preferences. Poverty estimations based on the welfarist approach typically rely on household consumption in terms of goods and services. The welfarist approach is closely linked to economic welfare and is therefore a monetary approach to poverty. In this context, one of the historically most common measures of poverty is the headcount ratio, which describes the number of poor as an estimated percentage of the total population (Ravallion, 1992).

An additional well-known measure is the poverty gap ratio, which describes the distance from the mean income of the poor to the poverty line. Generally, good poverty measures must fulfill certain requirements and axioms. One such axiom is the transfer axiom, which requires that an income transfer from a person below the poverty line to anyone who is richer must increase the poverty measure. In this regard, both previously mentioned measures are insufficient, as they violate the transfer axiom and do not reveal any information about the specific income distribution among the poor (Sen, 1976). Foster, Greer, and Thorbecke (1984) presented a more complete poverty index in line with the requirements proposed by Sen. At the heart of every poverty analysis in the welfarist sense are well-defined standards of consumption which determine whether an individual should be counted as poor or not. These standards are described by the poverty line. In developing countries, the use of an absolute poverty line is most common (Ravallion, 1992). Such an absolute poverty line is often defined as the cost of a specific basket of goods of necessities (Corak, 2006a). Relative poverty lines are mostly used for developed countries and are described as possessing a percentage of the national mean income (Ravallion, 1992).

More relevant for this dissertation than the welfarist approach is the non-welfarist approach. The non-welfarist approach moves away from centering the poverty measure on income or consumption and is multidimensional. It analyses specific forms of commodity deprivation, such as undernourishment or poor housing (Ravallion, 1992). Associated with the non-welfarist approach is Sen (1985, 1987). He questions the use of a money-metric approach based on utilities and argues in favor of a poverty definition in terms of a fixed set of capabilities. One of the first attempts to measure poverty in a multidimensional sense was made by Townsend (1979), who introduced deprivation indicators by analyzing access to items that can be considered as essential. Besides, several researchers have based their studies on asset-based indices and compared them to expenditure data (Booysen, Sahn & Stifel, 2000; Van Der Berg, Burger, Von Maltitz & Du Rand, 2008; Von Maltzahn & Durrheim, 2008). Asset-based indices have suggested that the ranking of household welfare differs from the one based on expenditure (Sahn & Stifel, 2000), promoting that conceptual differences between the two approaches exist.

A third approach to measuring poverty is based on subjective well-being (White, Leavy & Masters, 2003). However, subjective measurements will not play an important part in this study and are relatively underrepresented in the child poverty literature.

Irrespective of the approach chosen, household surveys are the most important source of data to assess living standards. These can either have the entire household or the individuals within a household as the unit of analysis. Deaton and Edmonds (1996) and Deaton (2003) have focused on how to best measure consumption in Living Standards Measurement Surveys, in which information on income or consumption is used as the standard indicator to measure living standards (Ravallion, 1992). Problems arise with respect to varying recall periods and how to measure individual welfare when consumption is only available at household level. Besides variables indicating consumption and income, which are important for welfarist approaches, household surveys contain information on health or housing conditions, which are crucial for multidimensional poverty analyses (Tsui, 2002).

3.1.2. Moving from Poverty to Child Poverty

Having discussed the different measurements of poverty within society, the focus of this literature review now shifts to child poverty. Why and since when do child poverty measures exist and how is it measured?

From the 1990s onwards, there was an increase in child poverty literature. It has been acknowledged that child welfare indicators differ from the standard welfare indicators for two reasons, rights and sustainability (White, Leavy & Masters, 2003). The acceptance of the Convention on the Rights of the Child by almost all countries in the 1990s has increased the importance of children in the poverty debate (Roelen & Gassmann, 2008). The Convention gives children the right to a childhood in which they can learn, play, enjoy full health and develop to their full potential (Minujin, Delamonica, Davidziuk & Gonzalez, 2006). White, Leavy, and Masters (2003, p.379) offer an interesting perspective by calling children the biggest "minority". In developing countries, between one-third and one-half of the population is younger than 15 years of age. At the same time, the limited political power of children bears the risk that their rights are not fulfilled. Poverty can deny children their fundamental rights, which can in turn cause severe and long-lasting damage (Gordon, Nandy, Pantazis, Townsend & Pemberton, 2003).

The second reason for centering the poverty debate separately on children is the sustainability aspect. The future of children's well-being critically depends on their current one. Comparatively low levels of well-being can thereby undermine capabilities and future potential to escape poverty (White, Leavy & Masters, 2003). The long-lasting consequences of poverty in childhood are further examined by Gordon et al. (2003), and Gordon and Nandy (2012), who argue that children are different from adults, and severe poverty can lead to lasting consequences. Children face increased risks of long-lasting consequences as childhood is a crucial period for mental, physical, and social development (Waddington, 2004). As the argument of the children's rights implicitly mentioned, children critically depend on their caretakers. Thereby, they face the risk of suffering from intra-household resource allocation (De Neubourg, Bradshaw, Chzhen, Main, Martorano & Menchini, 2012a; Roelen & Gassmann, 2008). Overall, development during childhood can be seriously hampered by poverty. It has also been shown that poor children are more likely to become poor adults (Corak, 2006b), with a potential mechanism being inter-generational poverty transmission (Waddington, 2004).

3.1.3. Measurement of Child Poverty

For the two main reasons of rights and sustainability, it is necessary to apply a different approach to child poverty than to general poverty. However, the question remains of how to best measure it. For decades, a debate has existed on whether to best measure poverty based on income and consumption or to apply a multidimensional measurement based on deprivations.

Like general poverty, child poverty has been measured from a welfarist and non-welfarist perspective. General welfarist approaches to measure poverty based on income and consumption are the headcount ratio, poverty gap ratio, and the FGT index, which have been presented previously. Solely focusing on income or consumption within the framework of the welfarist approach is unidimensional (Roelen & Gassmann, 2008) and has mostly been applied in developed countries. Thereby, the income measure is typically based on the entire household as a unit, which results in children being classified as poor if they live in a poor household (White, Leavy & Masters, 2003). Following this methodology, the number of children living in poverty in developed countries is identical to estimating the share of children living in poor households (Bradbury & Jäntti, 1999), which is not child-specific and does not account for the intra-household resource allocation (De Neubourg et al., 2012a; Roelen & Gassmann, 2008).

In developing countries, child poverty measurement should follow a broad-based approach (White, Leavy & Masters, 2003). This view is supported in a UNDP report (2022) and is part of the world development report (World Bank, 2001). The concept of multidimensional poverty as an SDG is relatively new. Within this framework, UNICEF developed a novel methodology called Multiple Overlapping Deprivation Analysis (MODA), which builds on previous multidimensional measurements and is the state of the art (De Miliano & Plavgo, 2018). Generally, there exist three different types of measurements of multidimensional child poverty. These are child poverty count measures, child poverty index measures, and holistic child poverty approaches (Roelen & Gassmann, 2008). The most used child poverty count measure is the Bristol approach, which relies on deprivation thresholds of several basic needs such as safe drinking water and shelter (Gordon et al., 2003; Gordon & Nandy, 2012). Child poverty index measures mostly build on the Alkire and Foster (2011) methodology, which enables an aggregation of the different dimensions of child poverty into a single index. This is based on a dual-cutoff strategy, with one being the dimension specific deprivation cutoff and the other one defining the threshold at which a person is considered poor. In contrast, the holistic child poverty measure does not aim to display one single poverty figure. Instead, it strives to present the complexity of child poverty based on quantitative as well as qualitative data (Young Lives, 2001).

MODA extends the existing child poverty measures by enabling subgroup comparisons and presenting their contribution to overall poverty, presenting deprivation overlaps, and facilitating cross-country comparisons. It builds on the Bristol-approach and the Alkire and Foster methodology (De Neubourg, Chai, De Milliano & Plavgo, 2012b). UNICEF has published a series of reports applying the MODA methodology in different regions of the world, including most Sub-Saharan African countries. These reports are single-country analyses and are comprehensive studies regarding the descriptive aspects of child poverty. They try to answer questions such as in which dimensions most children are deprived, which age groups suffer from which deprivations, or which deprivations are experienced simultaneously. Depending on data availability, the multidimensional analysis is complemented by a monetary unidimensional child poverty analysis. However, the reports have several shortcomings. The main limitations are that most of the reports are missing analyses on the marginal effects of the determinants of child poverty, which are usually discussed in the child poverty literature. Moreover, the reports tend to be comprehensive studies of the descriptive aspects of child poverty, but entirely miss an analysis of causal mechanisms.

Before turning to the determinants of child poverty, the advantages, and disadvantages of monetary and multidimensional approaches are shortly discussed. Measuring child poverty based on income or consumption has the advantages of revealing a quantifiable output, simplicity, and a straightforward interpretation. On the other hand, it is a unidimensional and not child-specific approach, which faces difficulties regarding comparability due to differences in survey design. The multidimensional poverty approach is child-specific and recognizes the complexity of child poverty, can be adapted depending on data availability, and analyzes overlaps of deprivations. Nevertheless, it also relies on the specific survey design and faces the issue that the most vulnerable groups are typically not included in the surveys (Roelen & Gassmann, 2008).

3.2. Determinants of Child Poverty

After presenting the theoretical ground for the analysis of child poverty, I will now examine the empirical findings regarding the determinants of child poverty. These can be classified into characteristics of the child, household, and community (White, Leavy & Masters, 2003).

3.2.1. Child Specific Characteristics

On the level of the child, it has been shown that older children are less likely to suffer severe poverty than younger children (Fonta et al., 2020; Lekobane & Roelen, 2020; Ministry of National Development Planning, 2018). The evidence for the impact of the child's gender is more ambiguous. Some studies revealed significant differences between genders. Lekobane and Roelen (2020) find that significantly more boys are identified as poor than girls in Botswana. To the contrary, Fonta et al. (2020), and UNICEF (2018) do not find a significant difference between genders in Burkina Faso and Rwanda. Therefore, the impact of gender seems to depend on the region-specific circumstances. This is confirmed by Ferrone and De Milliano (2018), who conducted their analysis in three Sub-Saharan African countries and found the gender to only affect the probability of being poor in Mali.

3.2.2. Household Specific Characteristics

On the household level, several demographic and socioeconomic characteristics of the household members, as well as the household composition are decisive factors in determining the probability of children living in poverty. Regarding the characteristics of the household head, some researchers have found gender to be significant (Belete, 2022; Lekobane & Roelen, 2020; Makhalima, 2020; Ministry of National Development Planning, 2018; UNICEF, 2018), whereas others find it to be insignificant (Ferrone & De Milliano, 2018). Within the studies that reveal a significant impact of the gender of the household head on the probability of children being poor, there exists ambiguity regarding the consequences of the genders. Some analyses reveal that children living in households with a man as the household head have a higher probability of being poor (Belete, 2022; Lekobane & Roelen, 2020). In contrast, Makhalima (2020) suggests that children living in male-headed households are less likely to be poor as males tend to be better off financially. This finding is in line with the general belief that female-headed households are more likely to be poor than male-headed households (Bradshaw, Chant & Linneker, 2017). The reasoning is the average pay difference between males and females (Barros, Fox & Mendonca, 1997).

A further demographic characteristic of the household head that has been included in some analyses is the age. Evidence suggests that children are significantly more likely to be poor if the household head is younger than 36 years (Lekobane & Roelen, 2020). In contrast, the age is found to be insignificant by Fonta et al. (2020).

Moreover, the marital status of the household head plays an important role. As with the other indicators, the evidence is contradictory. Lekobane and Roelen (2020) find that children living in a household with married parents are less likely to be poor, which one would probably expect, whereas Makhalima (2020) reveals that children living in households in which the head of household is divorced, are less likely to be poor.

Moving away from the demographic characteristics of the child, household head, and mother, the educational and employment status of the household head and mother are examined. Higher education of the parents reduces the risk of a child being poor (Chen & Corak, 2008). One would expect the educational status of the household head to be significant and negatively correlated with poverty. The child poverty literature confirms this (Lekobane & Roelen, 2020; Ministry of National Development Planning, 2018; National Bureau of Statistics (NBS) and United Nations Children's Fund (UNICEF), 2016; UNICEF, 2018) and describes it as one of the most important drivers of child poverty. It was shown that the completion of primary schooling by the household head in three Sub-Saharan African countries significantly decreases the probability of a child being deprived (Ferrone & De Milliano, 2018). However, contradictory findings exist as the educational status of the household head was found to be insignificant in Burkina Faso (Fonta et al., 2020). In contrast to the role of the educational level of the household head, the importance of the mother's educational level is indisputable. The higher the educational level of the mother, the lower the risk of children being poor (De Milliano & Plavgo, 2018; Ministry of National Development Planning, 2018; UNICEF, 2018; National Bureau of Statistics (NBS) and United Nations Children's Fund (UNICEF), 2018).

The probability of a child being poor decreases if the household head and the child's mother are employed (Chen & Corak, 2008; Ferrone & De Milliano, 2018; Lekobane & Roelen, 2020). Besides, the impact of employment on the probability of a child being poor also depends on the sector that the household head works in. The study of three Sub-Saharan African countries shows that especially employment in the agricultural sector can have detrimental effects on children (Ferrone & De Milliano, 2018).

The last aspect regarding the specific household composition is the number of children in the household and overall household size. The more children live in a household, the more likely it is for a child to be poor (Chen & Corak, 2008; De Miliano & Plavgo, 2018, Ministry of National Development Planning, 2018). Some have suggested the same relationship for household size and child poverty (Lekobane & Roelen, 2020; Makhalima, 2020). Others have argued that living in a large household reduces the risk of being poor (Fonta et al., 2020).

3.2.3. Community Specific Characteristics

On the community level, the area of residence plays the most important role. The consensus is that children living in rural areas are more likely to be poor than children living in urban areas (Belete, 2022; Fonta et al., 2020; Lekobane & Roelen, 2020; UNICEF, 2018; National Bureau of Statistics (NBS) and United Nations Children's Fund (UNICEF), 2018).

As the review revealed, some of the determinants of child poverty are similar across different contexts, and some vary in their magnitude or even direction. Therefore, one can conclude that the determinants of child poverty critically depend on the specific circumstances the household lives in and varies between countries. These significant differences between the determinants of child poverty in different regions and countries warrants for an analysis of the country-specific determinants of child poverty. Thereby, the determinants of poverty in Zambia have been relatively understudied. There exist only a few studies which have examined the determinants of poverty in Zambia. Daka and Fandamu (2016) recognize the multidimensional nature of poverty and analyze demographic and socioeconomic determinants by applying a logit model based on data from the 2013-2014 Demographic and Health Survey. Besides, Zambia is included in a study of the determinants of poverty in 48 Sub-Saharan African countries (Adeyemi, Ijaiya & Raheem, 2009). However, both papers examine general poverty and do not account for the crucial differences between child and general poverty. To my best knowledge, only one report, published by the Ministry of National Development Planning in cooperation with UNICEF (2018) focuses on child poverty specifically, applying the MODA methodology. Even though the report is very comprehensive regarding the descriptive aspects, it misses a detailed analysis of the determinants. Whereas only a couple of characteristics for each age group are discussed as determinants, the child poverty literature suggests many more demographic and socioeconomic determinants, which have not received any attention. Besides the report on child poverty in Zambia, other publications address the topic partly. These deal with the determinants of the nutritional status (Masiye, Chama, Chitah & Jonsson, 2010) and access to improved water sources (Mulenga, Bwalya & Chishimba, 2017), which are two of the dimensions typically included in a multidimensional child poverty analysis.

3.3. Impact of Rural-to-Urban Migration on Child Poverty

The previous review suggests that living in rural areas significantly increases the probability of children being poor. This raises the question of whether migrating from rural to urban areas significantly reduces children's risk of being poor in the short term. The discourse on rural-to-urban migration is relatively understudied in Sub-Saharan Africa (De Brauw, Mueller & Lee, 2014). One reason could be that migration is circular in many developing countries. If migrants do not settle permanently and remain closely linked to their area of origin, the group of rural-to-urban migrants becomes difficult to study (Haan, 1997). Existing research has mostly applied a Propensity Score Matching (PSM) analysis to estimate the causal effects of rural-to-urban migration (Deng & Law, 2020; Duda, Fasse & Grote, 2018; Kousar, Farah, Sadaf, Adil, Shahid & Mushtaq, 2016). A PSM analysis is well-suited for studying the effects of rural-to-urban migration as it incorporates that migration is not a random but selective process (Haan, 1997; Mulcahy & Kollamparambil, 2016).

Internal migration describes a process of displacement of people within a country, who migrate mostly for better employment opportunities (Duda, Fasse & Grote, 2018; Kousar et al., 2016). Some studies have focused on the causal impact of rural-to-urban migration on economic well-being. Regarding the economic consequences of rural-to-urban migration, in Ethiopia, it has been found that migrants are perceived to be better-off economically after migrating (Atnafu, Oucho & Zeitlyn, 2014). Similar finding exists in the context of Vietnam, where rural-to-urban migration has positive income growth effects (Nguyen, Raabe & Grote, 2015) and in Pakistan, where improved employment opportunities lead to migrant workers being better off after migrating (Mukhtar et al., 2018). A major driver of internal migration is extreme poverty (Atnafu, Oucho & Zeitlyn, 2014), underlining that the group of migrants is not random but self-selected. However, the migration of extremely poor households can lead to increasing poverty levels in urban areas. Thereby, rural-to-urban migration increases the pressure on urban infrastructures and contributes to rising levels of urban poverty (Awumbila, Owusu & Teye, 2014). Studies in Bangladesh and Burkina Faso have shown, that significantly more rural-to-urban migrants settle in slums as compared to other places (Fonta et al., 2020; Islam & Azad, 2007; Ullah, 2004). Sub-Saharan Africa is one of the regions with the highest share of the urban population residing in slums (UN-Habitat, 2014). These areas are considered low-cost housing areas with a very low standard of living, characterized by poor sanitary conditions. Besides, they receive little help from the authorities (Fonta et al., 2020). For the case of Zambia, it has been argued that living in informal settlements in urban areas in Zambia limits the residents' ability of improving their lives (Mwamba & Peng, 2020). Considering that rural-to-urban migrants are likely to settle in poorly planned areas as well as the high concentration of slums in Sub-Saharan Africa, rural-to-urban migrants are not only not guaranteed any welfare improvements, but they are at risk to decrease their well-being after migration.

In addition to the literature discussing the economic outcomes of rural-to-urban migration, there exist studies analyzing the effect of rural-to-urban migration on basic needs such as food security (Duda, Fasse & Grote, 2018) and health (Capazario & Kollamparambil, 2022; Deng & Law, 2020), which are also commonly included in multidimensional poverty indices. In the context of Tanzania, rural-to-urban migration decreases the food security of the households that remain in rural areas (Duda, Fasse & Grote, 2018). As shown previously, rural-to-urban migration tends to increase the reported well-being of migrants. However, when focusing on physical and mental health, migrants perceive themselves to be worse off than previously, some of the channels being social isolation and difficult living conditions (Capazario & Kollamparambil, 2022). Mulcahy and Kollamparambil (2016) similarly find decreases in subjective well-being. Besides social isolation and difficult living conditions, they mention false expectations and the emotional cost of leaving the home environment as crucial factors.

The effects of rural-to-urban migration are summed up by likely occurring economic benefits from migration but potentially decreasing health and subjective well-being outcomes. However, positive economic effects are not guaranteed, as migration increases the pressure on urban infrastructures and rural-to-urban migrants are likely to end up in slums or informal settlements. Generally, the entire literature discussed focuses on the outcomes of rural-to-urban migration on families, households, or employment seekers. As presented in section 3.1.2, it is necessary to apply a different approach to child poverty relative to general poverty. This must be recognized in the rural-to-urban migration literature and more child-specific studies are needed. To my best knowledge, publications on the causal effects of rural-to-urban migration are limited. So far, no study has researched the impact of rural-to-urban migration on child poverty. The only child-specific studies in this context analyze child outcomes from rural-to-urban migration on education (Zhang, 2017) and child survival (Brockerhoff, 1994; Islam & Azad, 2008). Therefore, besides the comprehensive analysis of the determinants of child poverty, this dissertation will contribute to the rural-to-urban migration literature by centering the debate on the child as an individual. Specifically, the causal effect of rural-to-urban migration on the probability of a child being poor in the short term will be estimated in Zambia.

4. Data

The analysis is based on data from the Living Conditions Monitoring Survey (LCMS) from Zambia in 2015, which was the seventh LCMS conducted since 1996. Data was collected in the months of April and May through face-to-face interviews using a structured electronic questionnaire. The survey covers a nationally representative sample of 62,879 individuals from 12,251 households from both rural and urban areas, including 31,472 children. Households from all ten Zambian provinces are included. The overall goal of the survey was to measure progress towards domestic and global development goals (Central Statistical Office, 2016). As previously mentioned, household surveys are the most important source of data to assess living standards (Deaton & Edmonds, 1996; Deaton, 2003; Ravallion, 1992) and surveys such as the LCMS are prevalent in the child poverty literature (Salecker, Ahmadov & Karimli, 2020; Roelen, 2017). The LCMS 2015 VII in Zambia is divided into 15 sections. These contain information on household roster, marital status and orphanhood, health, education, economic activity, income, household assets, household amenities and housing conditions, household access to facilities, agricultural production, household expenditure, developmental issues, child health and nutrition, deaths in the household, and self-assessed poverty.

Overall, the data is well-suited for the following analysis of multidimensional child poverty in Zambia. The survey is nationally representative, covers relevant dimensions across 15 sections, and is the most recent survey conducted in this context. However, some shortcomings exist. The main ones are insufficient information on the biological mother of children, relatively low data quality regarding the continuous variables of weight and height, and a missing comprehensive variable indicating income or consumption. Therefore, the following estimations will solely deal with multidimensional child poverty.

5. Methodology

The methodology consists of three parts. The first part presents the construction of the multidimensional child poverty index. The second part deals with the determinants of multidimensional child poverty in Zambia, and the third part with the causal effect of rural-to-urban migration on multidimensional child poverty.

5.1. Construction of the Multidimensional Child Poverty Index

The construction of the binary multidimensional child poverty index is at the heart of this analysis. As mentioned previously, child poverty indices are mostly built on the Alkire and Foster (2011) methodology, which allows for the aggregation of the different dimensions of child poverty into a single index. The estimation of the multidimensional child poverty index follows the approach developed by the Zambian Ministry of National Development Planning (2018), who have conducted a country-specific study of multidimensional child poverty in Zambia using the Z-MODA methodology. As the Alkire and Foster (2011) methodology suggests, a dual-cut-off strategy is applied.

The MODA methodology is anchored in the Convention of the Rights of the Child, defining children as poor if they are deprived of basic goods and services that are crucial for them. Moreover, it respects the different needs of children at different ages, which is why children are divided into three age groups 0 to 4, 5 to 13, and 14 to 17. Thereby, the dimensions used to calculate the index differ between age groups. The dimensions, indicators, and cut-offs were defined by sectoral experts in Zambia, national standards, research interests, and data feasibility. An overview of the dimensions and indicators is shown in *Table 1*, and a detailed description of the specific cut-offs for each indicator in *Table A.1* in the appendix.

Each age group is characterized by individual and household-level characteristics. The four dimensions that are identical throughout all groups are information, housing, sanitation, and water, which are all household-level indicators. Individual-level dimensions differ, with only the two older age groups being analyzed regarding education and child protection and only the youngest cohort regarding nutrition and health. Each dimension contains one to two indicators, with a child being deprived in a given dimension if it is deprived in at least one indicator of this dimension. This implies that MODA uses the union approach, which means that the number of indicators per dimension impacts the risk of considering someone as poor. It is therefore important to have similar numbers of indicators across dimensions, which is given in this case. Moreover, the union approach assigns identical weights to all indicators within a dimension

(De Neubourg et al., 2012b). One limitation is that it does not account for potentially different importance of the indicators within one dimension, or the severity of deprivation in any given indicator.

Table 1: Overview of Dimensions and Indicators

Children aged 0-4 years		**Children aged 5-13 years**		**Children aged 14-17 years**	
Dimensions	*Indicators*	*Dimensions*	*Indicators*	*Dimensions*	*Indicators*
Nutrition	• Infant and young child feeding • Weight-for-height indicator	**Child Protection**	• Child marriage/ cohabitation • Child labor	**Child Protection**	• Child marriage/ cohabitation • Child labor
Health	• Full immunization	**Education**	• Compulsory school attendance • Grade-for-age	**Education**	• Grade-for-age • Primary school attainment
Information	• Availability of information devices	**Information**	• Availability of information devices	**Information**	• Availability of information devices
Housing	• Overcrowding • Housing materials	**Housing**	• Overcrowding • Housing materials	**Housing**	• Overcrowding • Housing materials
Sanitation	• Access to improved sanitation • Garbage disposal	**Sanitation**	• Access to improved sanitation • Garbage disposal	**Sanitation**	• Access to improved sanitation • Garbage disposal
Water	• Drinking water source • Water treatment	**Water**	• Drinking water source • Water treatment	**Water**	• Drinking water source • Water treatment

Source: Adapted from Ministry of National Development Planning (2018)

Once all indicators and dimensions are estimated for all children, the second cut-off is made, dealing with the question of when to consider a child as poor. For the following analysis, the cut-off is made at three deprivations, meaning that a child is considered poor if deprived in at least three out of six dimensions (Ministry of National Development Planning, 2018). Even though the Ministry of National Development Planning (2018) also bases its report on the 2015 LCMS VII survey, our estimated deprivations are not identical to the ones found in the report. One reason is that their dataset slightly differs from the one utilized in this study. Besides, it is likely that the included observations and chosen cut-offs for each indicator slightly differ between the report and this dissertation. This leads to slightly different estimates. Once the cut-offs for each indicator and dimension are defined, the multidimensional poverty index takes on the value 1 if a child is deprived in at least three dimensions, and value 0 if it is deprived in less than three dimensions.

5.2. Determinants of Multidimensional Child Poverty

Once the multidimensional child poverty index is estimated, the determinants of multidimensional child poverty in Zambia are examined using the probit model. The specific model is:

$$\Pr(y_i = 1 \mid x) = \Phi\,(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5) \qquad (1)$$

The dependent variable y_i is the binary multidimensional child poverty index, taking on either value 1 if a child is multidimensionally poor or 0 if it is not. In the probit model, the dependent variable is described by $\Pr(y_i = 1 \mid x)$, which is the probability of observing a value of 1 of y_i, given the values of the independent variables of the vectors $X_1$to X_5.

Φ is the cumulative distribution function of the standard normal distribution. The constant is described by β_0 and the regression coefficients by β_1 to β_5. The independent variables chosen are those that are commonly used in the literature and are described by the five vectors X_1 to X_5. The model contains some continuous as well as dichotomous variables. However, following the child poverty literature, some continuous variables such as age or education are grouped into several dummy variables (Lekobane & Roelen, 2020; Salecker, Ahmadov & Karimli, 2020).

The first vector X_1 contains child characteristics. A dichotomous variable indicating the gender of the child is included, taking on the value 1 if a child is male and 0 if it is female. Besides, three age groups are included in the analysis. One dummy variable takes on a value of 1 if a child is aged 5 to 13 and 0 otherwise, and another dummy takes on a value of 1 if a child is aged 14 to 17 and 0 otherwise. Children aged 0 to 4 years are excluded as the reference group.

The second vector X_2 includes demographic and socioeconomic characteristics of the household head. Regarding the demographic characteristics, a dichotomous variable indicates the gender and takes on the value 1 if the household head is male and 0 otherwise. As with child characteristics, different dummy variables indicating age are included, excluding one group as the reference group. The age classification follows Lekobane and Roelen (2020), who split the ages of the household head into children (12-17 years), youth (18-35 years), adults (36-64 years), and older persons (65+ years). The two dummy variables included are if the household head is younger than 36 years and older than 65 years of age. The age group from 36 to 65 represents the reference group. Additionally, the marital status is included in the model. As before, dummy variables are included, which either take on the value 1 or 0 depending on the marital status. The reference group of married household heads is excluded from the model, whereas dummy variables for the household head being never married, separated, divorced, widowed, or cohabitating are included.

Regarding the socioeconomic characteristics of the household head, variables indicating education and employment are included. The reference group for the educational attainment are household heads who have not received any formal schooling. The regression contains three dummy variables for primary, secondary, and tertiary school attainment, taking on the value 1 if the specific level was attained and 0 otherwise. Regarding employment, a dummy variable of value 1 indicates that the household head is in wage employment, whereas a value of 0 represents self-employment.

The third vector X_3 contains socioeconomic characteristics of the mother. However, a significant limitation due to data availability is that information on the biological mother is only available for children younger than five years. Even for these children, the only information available is if the biological mother is alive and if she lives in the same household. This is insufficient information to help in identifying which of the household members is the mother as a household may contain up to 29 members. Besides, information on the biological mother of children older than five years is missing completely. However, as the literature suggests that the socioeconomic characteristics of the mother are significant determinants of child poverty, it is crucial to include mother characteristics in the model. For the following analysis, the mother's characteristics are proxied with the ones of the household head if the household head is female. If the household head is male, they are proxied with the ones of the spouse. This relies on the assumption that the household head or his spouse respectively has a major role in the upbringing of the children. This assumption is reasonable in the context of Zambia, where the household head is usually responsible for day-to-day decisions concerning the household (Central Statistical Office, 2016). As household decisions directly affect children, it can be assumed that depending on household composition, the household head or his spouse is the household member who comes closest to the mother's role in decision-making during upbringing. The model includes the education and employment status of the mother. Regarding education, the model follows the same approach as with the household head, with mothers who have not received any formal education being the reference group, and three dummy variables indicating if the highest educational attainment of the mother was primary, secondary, or tertiary schooling. Regarding the occupational status, the reference group are self-employed mothers, and two dummy variables are included taking on the value 1 if the mother is in wage employment or an unpaid family worker respectively, and 0 otherwise.

Moving away from the specific characteristics of individual household members, the fourth vector X_4 describes household characteristics. Two continuous variables are included in the model, one indicating the number of household members and the other one the number of children in the household.

Lastly, the fifth vector X_5 contains regional characteristics. A dichotomous variable indicates whether the household resides in an urban or rural location. Additionally, nine dummy variables are included for the provinces Central, Copperbelt, Eastern, Luapula, Lusaka, Muchinga, Northern, North-Western, and Southern, accounting for regional fixed effects. Western is excluded from the model as the reference group. It is important to note that the error term of a probit model is assumed to follow a normal distribution. An overview of the variables used for the estimation is provided in *Table A.2* in the appendix.

5.3. Impact of Rural-to-Urban Migration on Multidimensional Child Poverty

After analyzing the correlates of child poverty, the rural and urban areas' determinants are further elaborated. The study now turns to examining the causal effect of rural-to-urban migration on child poverty. Generally, migration depends on a self-selected process and is not randomly assigned. Because of that, the characteristics of the groups of migrants and non-migrants differ, leading to biased comparisons (Mukhtar et al., 2018). In such a scenario, Propensity Score Matching (PSM) is a well-suited method to estimate causal effects (Garrido, Kelley, Paris, Roza, Meier, Morrison & Aldridge, 2014), often applied in the rural-to-urban migration literature (Capazario & Kollamparambil, 2022; Duda, Fasse & Grote, 2018; Kousar et al., 2016). The idea behind PSM is to account for observed confounding factors (Capazario & Kollamparambil, 2022) by comparing outcomes of treated and untreated individuals, which are as similar as possible (Kousar et al., 2016). In this case, the treatment variable is the rural-to-urban migration of children. This is a dichotomous variable taking on the value 1 if a child has moved from a rural to an urban location within the past 12 months, and value 0 if it has remained in a rural location. Therefore, only children that initially resided in rural areas are considered for the analysis of the causal effects of rural-to-urban migration.

PSM contains three steps (Duda, Fasse & Grote, 2018). The first is to calculate the propensity score for each individual (Lunt, 2014), which corresponds to $p(X) = \Pr\{Tr = 1 \mid X\}$. $Tr = \{0,1\}$ indicates treatment group selection. The vector X contains all relevant confounding factors. Given all confounding factors, the propensity score is the probability of an individual being selected into the treatment group (Rosenbaum & Rubin, 1983). As the treatment is indicated by a binary variable, the propensity score is estimated with a logit or probit model, respectively. Generally, both models lead to similar results and the choice of the specific model is not crucial (Caliendo & Kopeinig, 2008). The following analysis reveals that the logistic regression model fits the data slightly better, which is why the PSM analysis is based on a propensity score estimated by a logistic regression model. As independent variables, the model should include only those variables, which simultaneously impact the treatment decision (rural-to-urban migration) and the outcome variable (multidimensional child poverty). Moreover, the model should contain all variables pre-treatment (Caliendo & Kopeinig, 2008).

$$\Pr(y_i = 1 \mid x_i) = \frac{\exp\,(\beta_0+\beta_1\,X_1+\beta_2\,X_2+\beta_3\,X_3+\beta_4\,X_4)}{1+\exp\,(\beta_0+\beta_1\,X_1+\beta_2\,X_2+\beta_3\,X_3+\beta_4\,X_4)} \qquad (2)$$

The model will follow the form presented in equation (2). The dependent variable is the treatment probability (Lunt, 2014), which in this study is the binary variable rural-to-urban migration, taking on the value 1 if a child has migrated from a rural-to-urban location within the past 12 months and 0 if it remained in a rural location.

The independent variables are all observable confounding factors available to us in the dataset, described by the vectors X_1 to X_4. I rely on previously conducted research to decide which confounding factors to include in the model. Besides characteristics of the household head, existing literature suggests the use of socioeconomic variables indicating household welfare and household-specific variables indicating household size and location. These are the core variables included in most models throughout the literature. Household welfare is expressed as the ownership of livestock or agricultural land, income, or asset indices respectively (Duda, Fasse & Grote, 2018; Kousar et al., 2016; Mukhtar et al., 2018; Nguyen, Raabe & Grote, 2015). Besides these confounding factors, some studies include additional indicators for economic and environmental shocks to the household (Duda, Fasse & Grote, 2018, Mukhtar et al., 2018). Unfortunately, this information is not available for the pre-treatment group. Adapting the models from previous research to the data available and the context studied, I control for the following confounding factors.

The child-specific variables of age and gender are controlled for by the vector X_1. Even though this is uncommon in the rural-to-urban migration literature, it is essential in the context of this study, as the child is at the center of the analysis and the matching procedure should account for child similarities and differences.

Regarding the characteristics of the household head (X_2), a variable indicating the age and age squared is included, which is in line with Deng and Law (2020). Besides, following Kousar et al. (2016) and Duda, Fasse, and Grote (2018), a dichotomous variable taking on the value 1 if the household head is male and 0 if female is included. As other studies control for the family type (Kousar et al., 2016), the marital status is included as a dummy variable taking on the value 1 if the household head is married and 0 if not, which is in line with (Capazario & Kollamparambil, 2022). Moving away from the demographic characteristics, the years of schooling are included as a continuous variable (Capazario & Kollamparambil, 2022; Duda, Fasse & Grote, 2018; Kousar et al., 2016).

Additionally, to account for household welfare, a household asset ownership index is included (X_3), which follows Duda, Fasse, and Grote (2018). The index is created using Multiple Correspondence Analysis (MCA). MCA is a method that aims to analyze a set of observations described by nominal variables, which all consist of several different levels. These levels are coded as binary variables, which either take on the value 1 or 0 (Abdi & Valentin, 2007). MCA has been found to be well-suited for estimating asset-based indices in low- and middle-income countries (Traissac & Martin-Prevel, 2012). The index is calculated based on over 60 assets, covering general items, kitchen and household items, tools and machines, transport items, and animals (overview in *Table A.3* in the appendix). Afterwards, five quintiles are generated, which indicate the wealth of an individual, with the wealthiest individuals being part of quintile 1. However, the asset index leads to a problem as PSM requires a matching of the confounding factors pre-treatment. Whereas all other variables considered are identical post- and pre-treatment, information on household welfare is only available post-treatment. However, it is essential to control for household welfare as ignoring it would lead to individuals being matched independent of their economic well-being, which could heavily bias the results. Therefore, to get around this limitation, I include the post-treatment household asset index. To do so, it must be reasonable to assume that the index remains relatively similar post-migration compared to pre-migration. Generally, this is given in this context as it is reasonable to assume that if households migrate, they take most of their belongings with them. Of course, the index might change slightly by leaving some assets behind or gaining new ones in the urban location. However, some assets are more likely to occur in an urban environment such as electric stoves, and others in rural environments, such as animals. Overall, these assets are relatively well-balanced. Therefore, it is reasonable to assume that some assets are left behind, while others are gained through migration, leaving the index relatively unchanged. However, a problem arises if migrating leads to higher or lower economic welfare, for instance, through changed employment opportunities in the urban location, which could increase or decrease the asset index post-migration and therefore bias the estimates if households move to a different quintile compared to pre-migration. Individuals who have reached a higher/lower quintile post-migration would then be matched with individuals in the same quintile without migration, thereby biasing the results. This issue will be further discussed in section 6.3, where a variable indicating the perceived well-being of children is used to further elaborate on the bias. However, the household asset index is not expected to change dramatically in the short term.

Lastly, as in Kousar et al. (2016) and Duda, Fasse, and Grote (2018), a continuous variable indicating household size and nine dummy variables for the provinces the household resided in pre-treatment are included. These are indicated by vector X_4. An overview of the variables used for the estimation of the propensity scores is found in *Table A.4* in the appendix. Following Rosenbaum and Rubin (1983), PSM will adequately predict causal effects, as it sufficiently removes bias of all observed confounding factors.

After estimating the propensity scores for each individual (treatment and potential control group members), the second step deals with creating comparison groups (Stone & Tang, 2013). This can be done in three ways: matching, stratification, and weighting (Lunt, 2014). The following analysis will contain all three methods. There are several different techniques to perform the matching. Greedy matching is applied, which starts by matching a treated individual to an untreated individual with the closest propensity score. Once these two are paired off, all remaining individuals are compared for propensity scores and the two closest individuals are matched again. This is done until all treated individuals are paired with an untreated individual. However, this scenario does not necessarily imply that all matches are of high quality. Even though the closest propensity scores are matched, they can still be relatively far apart. Therefore, a caliper is applied, restricting the matches to a chosen distance threshold between the propensity scores of the treated and untreated individuals. Treated individuals with no comparable untreated individual within this caliper are excluded from further estimations. The second method, stratification, ranks all individuals regarding their propensity score and creates subgroups of individuals called stratas (Lunt, 2014). The entire sample is divided into five stratas, which removes about 90% of the bias caused by the confounding factors (Cochran, 1968). Afterwards, the effect of treatment is assessed for each stratum. The third method, weighting, is based on reweighting all confounding factors so that all confounders are well-balanced (Lunt, 2014). This dissertation applies the weight of the standardized mortality ratio (SMR).

In the third and last step, the Average Treatment Effect on the Treated (ATT) is estimated (Duda, Fasse & Grote, 2018). This effect is described as:

$$ATT = \tau_{ATT}^{PSM} = E\,\{E\,[\,Y_1 \mid M = 1, p(X)] - E\,[Y_0 \mid M = 0, p(X)] \mid M = 1\} \qquad (3)$$

The ATT is estimated using PSM, with M being the binary rural-to-urban migration status, which is equal to 1 if a child migrated and 0 if it did not. The outcome for the treated group is represented by Y_1, and for the control group by Y_0, given the propensity score $p(X)$.

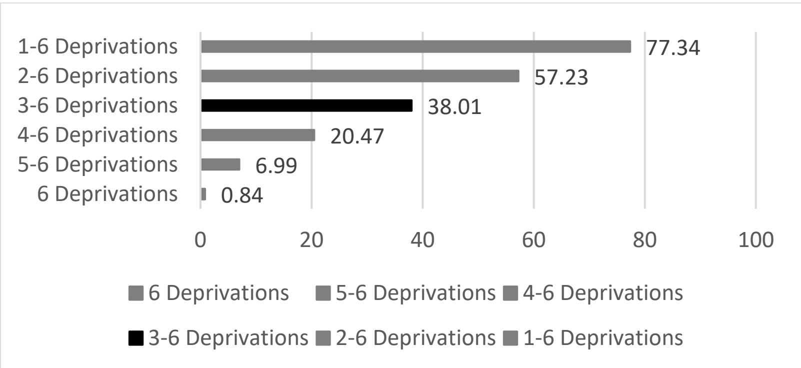
6. Estimation Results

This section is divided into three subsections. Firstly, the deprivations of the different dimensions of multidimensional child poverty are presented. Secondly, the estimation results for the determinants of multidimensional child poverty are assessed. After conducting robustness checks, the third subsection deals with estimating the causal effect of rural-to-urban migration on child poverty.

6.1. A Detailed Analysis of the Multidimensional Child Poverty Index

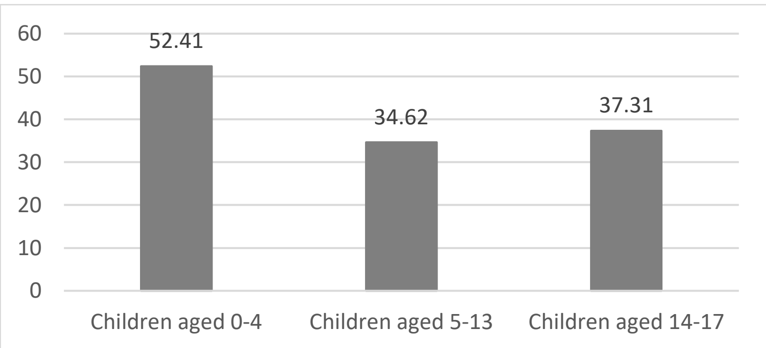
Before discussing the determinants of multidimensional child poverty, it is crucial to have a good understanding of the multidimensional child poverty index. As *figure 5* shows, more than three-fourths of all children are deprived in at least one out of six dimensions. 38% of children are deprived in at least three dimensions, which represents the chosen cut-off for considering a child as poor. Lastly, 1% of the children are extremely poor and are deprived in all six dimensions. Regarding the three age groups, one observes that especially the youngest group is affected by poverty, indicating a headcount ratio of over 52% being deprived in at least three dimensions, compared to about 35% and 37% of the older two age groups (*figure 6*).

Figure 5: Multidimensional Deprivation Headcount in % of All Children



Source: Author's calculations using Zambia LCMS (2015)

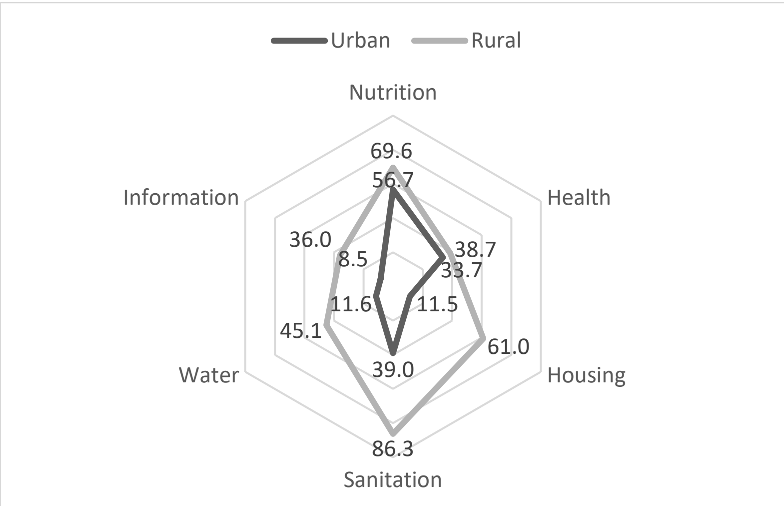
Figure 6: % of Children Deprived in at Least Three Dimensions



Source: Author's calculations using Zambia LCMS (2015)

Moreover, the structure of child deprivation will be examined separately for each age group and for rural and urban areas. A more detailed analysis of the deprivation headcounts of each indicator within each dimension for the three age groups is found in *figure A.1* in the appendix. Throughout all three age groups and each of the dimensions, it stands out that significantly more children are deprived in rural than in urban areas. Regarding the youngest group, which has been shown to be the group with most children suffering from multidimensional poverty, *figure 7* displays that deprivations are especially high in the two dimensions of sanitation and nutrition. Whereas nutrition is also a problem in urban areas, deprivations in sanitation are mostly prevalent in rural areas. Moreover, the number of children deprived of water and housing is also relatively high but affects mostly children in rural areas. Fewer children are deprived with regards to health and information.

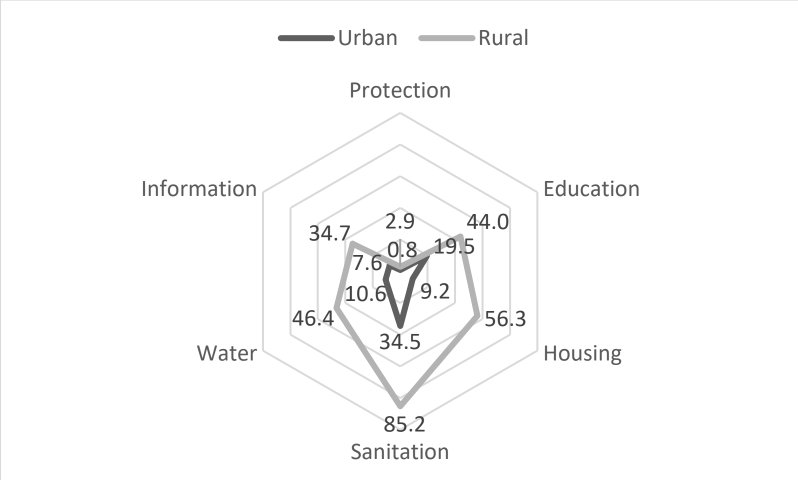
Figure 7: Children Deprived in Each Dimension as % of All Children in that Age Group (Children Aged 0-4)



Source: Author's calculations using Zambia LCMS (2015)

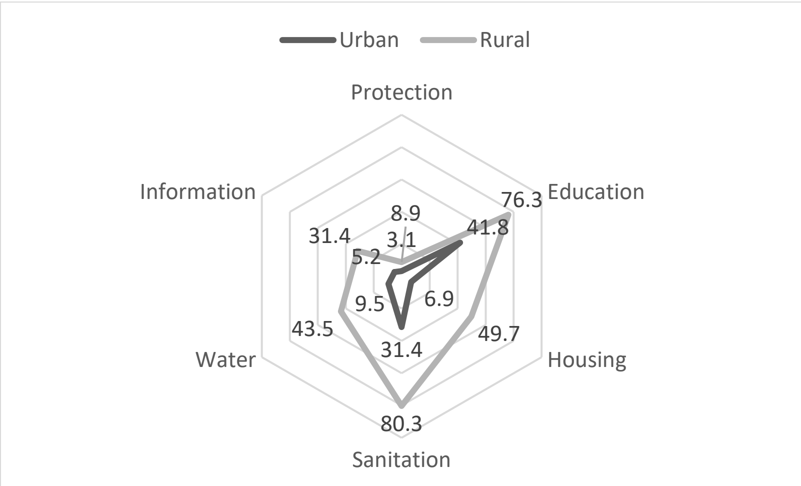
Figures 8 and *9* show that very few children are deprived of child protection in the age group of children aged 5 to 13 as well as children aged 14 to 17. The deprivations in the dimensions of information, water, sanitation, and housing are very similar across the two age groups. Moreover, sanitation in rural areas presents an issue. A relatively large discrepancy between the two age groups exists regarding education, in which relatively more children of the oldest age group are deprived.

Figure 8: Children Deprived in Each Dimension as % of All Children in that Age Group (Children Aged 5-13)



Source: Author's calculations using Zambia LCMS (2015)

Figure 9: Children Deprived in Each Dimension as % of All Children in that Age Group (Children Aged 14-17)



Source: Author's calculations using Zambia LCMS (2015)

Overall, the share of multidimensionally poor children remains high. Thereby, especially young children are affected by poverty. Moreover, a huge discrepancy exists between children in rural and urban areas. More children are affected by poverty in rural areas, with sanitation being the dimension in which most children are deprived.

6.2. Determinants of Multidimensional Child Poverty in Zambia

For a more comprehensive understanding of the characteristics of poor children in Zambia, probit and logit models are estimated with the binary variable of multidimensional child poverty as the dependent variable. *Table A.5* in the appendix contains the descriptive statistics. As both the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC), suggest that the probit model fits the data better, I proceed with the probit model. An overview of the

AIC and BIC is found in *Tables A.6* and *A.7* in the appendix. The estimated coefficients of the probit model and the average marginal effects are presented in *Table 2*.

The interpretation of the coefficients in a probit model is limited compared to linear regression or logistic regression models. Nevertheless, the coefficient helps to elaborate on the significance of the independent variables and the direction of their correlation with the dependent variable. A positive coefficient reveals that an increase in the predictor leads to an increase in the predicted probabilities, whereas a negative coefficient has the opposite effect on the predicted probabilities (Statistical Methods and Data Analytics, 2021).

To better interpret the determinants of child poverty and examine their magnitude, average marginal effects (*Table 2*) and marginal effects at the mean (*Table A.8* in the appendix) are estimated. The marginal effect at the mean is the marginal effect of a given determinant, calculated at the mean value of this determinant. A disadvantage of interpreting the marginal effect at the mean is that no individual necessarily exists, which is characterized by exactly this mean value (Onukwugha, Bergtold & Jain, 2015). Whereas this is less problematic with continuous variables, it hinders an interpretation of the marginal effects of dummy variables. For instance, the mean of the dichotomous child gender variable is equal to 0.49. As no such individual exists in the dataset, the interpretation is not satisfactory. In contrast, the average marginal effect is calculated by estimating the marginal effect for each observation, which is then averaged across all observations (Onukwugha, Bergtold & Jain, 2015). This is the preferred interpretation of the marginal effect. In the following, all average marginal effects are interpreted ceteris paribus (all other independent variables remain constant).

Regarding the main variable of interest of this dissertation, *Table 2* shows that children who live in rural areas have a significantly higher predicted probability of being poor than children residing in an urban environment. The average marginal effect suggests that living in an urban area decreases the probability of a child being poor by 28 percentage points on average compared to living in rural areas. This confirms our previous observations from section 6.1. Depending on the specific province, some children are more likely to be poor than others.

Regarding further determinants, child-specific characteristics of age and gender are statistically significant at a 1% significance level. Whereas being an older child tends to reduce the risk of being poor, being male increases the predicted probability. The probability of being poor decreases on average by 17 percentage points if a child is aged 5 to 13 years compared to a child aged 0 to 4 years. Similarly, the probability of being poor decreases on average by nine percentage points if a child is aged 14 to 17 years compared to a child aged 0 to 4 years.

Additionally, male children have two percentage points slightly higher probability of being poor on average than female children.

Regarding the characteristics of the household head, gender, and marital status are statistically insignificant. However, as the proxied characteristics of the mother are included in the model, only female household heads and male household heads with a spouse are considered in the analysis, which could potentially affect the estimates of the marital status. Therefore, an estimation of the probit model excluding mother characteristics to check for the robustness of the estimates for the marital status is included in *Table A.9* in the appendix. The results remain mostly unchanged. Whereas the gender, never married, separated, divorced, and widowed remain statistically insignificant, cohabitating is now a significant determinant, but only under a 10% significance level.

Regarding the demographic characteristics of the household head, age is the only significant determinant. Compared to living in a household with a household head aged 36 to 65, living with a household head aged younger than 36 increases the probability of a child being poor by four percentage points on average. Similarly, living with a household head aged older than 65 increases the probability of a child being poor by three percentage points on average compared to the reference group.

Moreover, the results show that the higher the education of the household head and mother, the lower the predicted probability of children being poor. The attainment of primary schooling by the household head decreases the probability on average by five percentage points, of secondary schooling by 13 percentage points, and of tertiary schooling by 33 percentage points compared to no formal education. Regarding the mother, the probability of a child being poor decreases by 6, 17, and 39 percentage points, respectively.

Regarding employment, it turns out that only the employment of the household head and not of the mother is a significant determinant of child poverty. Living with a household head who is in wage employment decreases the probability of being poor for children by an average 11 percentage points compared to living with a self-employed household head.

Both household size and the number of children in the household are statistically significant determinants of child poverty. The predicted probability of being poor increases by, on average, two percentage points for an additional child in the household. At the same time, the probability of a child being poor decreases by about two percentage points on average for an additional household member.

Table 2: The Effect of Determinants on Multidimensional Child Poverty. Probit Estimation

	Dependent Variable: Multidimensional child poverty	
Independent Variables	Coefficients	Average Marginal Effects
Child gender	0.063***	0.016***
	(0.022)	(0.006)
Child aged 5-13 years	-0.679***	-0.174***
	(0.033)	(0.008)
Child aged 14-17 years	-0.355***	-0.091***
	(0.039)	(0.010)
HH gender	-0.013	-0.003
	(0.058)	(0.015)
HH aged 35 years or younger	0.150***	0.039***
	(0.029)	(0.007)
HH aged older than 65 years	0.113**	0.029**
	(0.048)	(0.012)
HH is never married	0.099	0.025
	(0.105)	(0.027)
HH is separated	0.142	0.036
	(0.087)	(0.022)
HH is divorced	0.090	0.023
	(0.071)	(0.018)
HH is widowed	0.056	0.014
	(0.065)	(0.017)
HH is cohabitating	0.506	0.130
	(0.486)	(0.125)
HH primary schooling	-0.182***	-0.047***
	(0.049)	(0.013)
HH secondary schooling	-0.509***	-0.131***
	(0.053)	(0.013)
HH tertiary schooling	-1.290***	-0.331***
	(0.122)	(0.031)
HH in wage-employment	-0.445***	-0.114***
	(0.045)	(0.011)
Mother primary schooling	-0.238***	-0.061***
	(0.039)	(0.010)
Mother secondary schooling	-0.673***	-0.173***
	(0.047)	(0.012)
Mother tertiary schooling	-1.536***	-0.394***
	(0.223)	(0.057)
Mother in wage-employment	-0.040	-0.010
	(0.058)	(0.015)
Mother is an unpaid family worker	0.034	0.009
	(0.029)	(0.007)
Number of household members	-0.088***	-0.023***
	(0.009)	(0.002)
Number of children in the household	0.079***	0.020***
	(0.011)	(0.003)
Residing in an urban location	-1.080***	-0.277***
	(0.030)	(0.007)
Central	-0.940***	-0.241***
	(0.054)	(0.014)
Copperbelt	-0.979***	-0.251***
	(0.055)	(0.014)
Eastern	-1.071***	-0.275***

	(0.051)	(0.013)
Luapula	-0.189***	-0.048***
	(0.052)	(0.013)
Lusaka	-1.481***	-0.380***
	(0.066)	(0.016)
Muchinga	-0.314***	-0.081***
	(0.053)	(0.014)
Northern	-0.076	-0.020
	(0.052)	(0.013)
North-Western	-0.606***	-0.155***
	(0.052)	(0.013)
Southern	-0.879***	-0.225***
	(0.050)	(0.012)
Constant	2.244***	
	(0.090)	
Observations	18,127	18,127

Source: Source: Author's calculations using Zambia LCMS (2015)
Note: Standard errors are reported in parentheses; *, ** and *** denotes statistical significance of 10%, 5%, and 1% respectively.

6.2.1. Robustness Checks

Even though the AIC and BIC suggest using a probit model over a logit model, it is crucial to elaborate on the model's accuracy. The robustness checks are reported in the appendix. Following the classification output (*Table A.10* in the appendix), the accuracy is adequate. The classification output compares the correspondence between the true group membership of poor and non-poor children and the one predicted by the model, resulting in an overall average value of 77.37% correct classifications. This is well-balanced between sensitivity and specificity, indicating that both groups are classified relatively well.

The link test (*Table A.11* in the appendix), a specification test for single-equation models, confirms the good fit of the model. The link test is used to detect specification errors. If the model is correctly specified, the variable _hat should be statistically significant and _hatsq insignificant (Zavras, Zavras, Kyriopoulos & Kyriopoulos, 2016). This is given in our case.

Additionally, the Receiver Operating Characteristic Curve (ROC Curve) is analyzed (*figure A.2* in the appendix). The ROC Curve displays a plot of the sensitivity versus 1-specificity of a diagnostic test. The area under the curve is well-suited to assess the overall diagnostic accuracy. Generally, the area under the curve takes values between 0 and 1. The closer the value is to 1, the better the discriminatory ability. In our case, the area is 0.86, which is considered excellent (Mandrekar, 2010).

To further elaborate on the model, I analyze the Kernel density function of the residuals (*figure A.3* in the appendix). The Kernel technique produces smooth probability density function estimates (Węglarczyk, 2018). As mentioned previously, a crucial assumption of any probit model is that the residuals are normally distributed. As the graph shows, the Kernel density estimate of the residuals is similar to a normal distribution. Overall, the robustness checks suggest that the probit model is well-specified, accurate, and fits the data well.

6.3. The Causal Effect of Rural-to-Urban Migration on Multidimensional Child Poverty

Living in rural areas stands out as a crucial determinant increasing the probability of many children being poor. This finding is elaborated on more thoroughly in the following analysis. More specifically, I examine the causal effects of rural-to-urban migration on child poverty using PSM[1]. Based on our previous finding, I expect rural-to-urban migration to decrease the probability of children being multidimensionally poor.

At first, the balance of the confounding factors is assessed (*Table A.16* in the appendix). One observes that the standardized differences for some confounding factors are minor, whereas others such as the years of education of the household head or the household asset index are relatively large. The analysis of the standardized differences confirms that the selection of treated individuals is not random but selective. Following the means in the treated and untreated group, migrating children come from a on average higher socioeconomic background opposed to children who do not migrate. Migrating children live with a household head who has about 2.5 more years of education and have higher household welfare on average, indicated by the lower asset index (quintile 1 contains the richest households and quintile 5 the poorest). Because of the presented self-selection into migration, PSM is needed to examine causal effects.

The estimated log propensity score is used for matching, stratification, and weighting. Matching is done in two ways, firstly without a caliper and secondly applying a caliper of 0.05. As *figures 10* and *11* display, applying a caliper of 0.05 leads to an exclusion of the comparably

[1] To assess which model to use for the estimation of the propensity scores, a logit and probit regression model is performed. The AIC and BIC suggest that the logit model fits the data better (*Tables A.12* and *A.13* in the appendix), which is why I continue with a logistic regression model for the estimation of the propensity score. The output of the logit model is found in *Table A.14* in the appendix. A Hosmer-Lemeshow test (*Table A.15* in the appendix) is applied to analyze the functional form of the model, which is the standard test for the goodness-of-fit of logistic regression models (Kuss, 2002). The test reveals a p-value of 0.36 and is therefore insignificant, meaning that the functional form of the model fits the data well (Baek, Park, Won, Park & Kim, 2015). The distribution of the propensity score is presented in *figure A.4* in the appendix. To have a distribution that comes closer to a normal distribution for both subgroups of treated and untreated individuals, I estimate the log propensity score, presented in *figure A.5* in the appendix, which is recommended by the literature (Lunt, 2014). As there is a high density of observations with a very low propensity score, the log propensity scores are distributed in the negative values. Most importantly, the area of common support is large.

high differences above 0.05 between matched treated and untreated individuals. However, this comes at the cost of excluding 13 treated individuals from the analysis due to missing comparable untreated individuals with a propensity score within the range of the caliper.

Figure 10: Difference in Log Propensity Scores

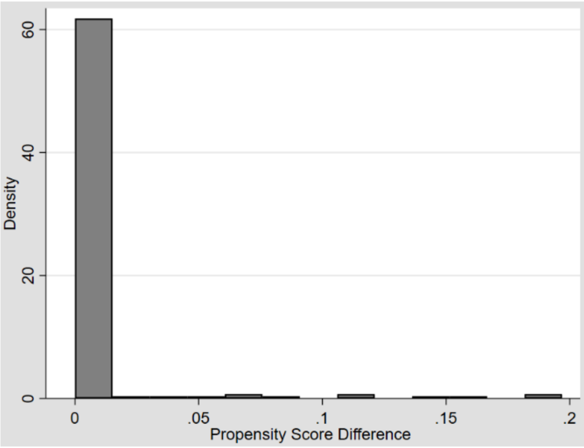
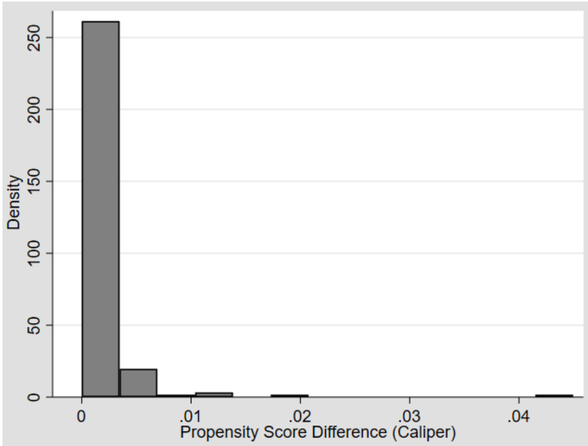


Figure 11: Difference in Log Prop. Scores (with Caliper)



Source: Author's calculations using Zambia LCMS (2015)

The results for all methods are displayed in *Table 3*. The idea behind estimating the causal effect using all four methods is to check for the robustness of the results, as every method has drawbacks and advantages. *Table 3* displays a highly statistically significant causal effect of rural-to-urban migration on child poverty under a 1% significance level throughout all specifications. The Average Treatment Effect on the Treated (ATT) ranges from -0.195 to -0.239 depending on the method used. Therefore, on average, participation in rural-to-urban migration in Zambia significantly decreases the probability of multidimensional child poverty by about 20 to 24 percentage points in the short run.

Table 3: Estimation of the Causal Effect of Rural-To-Urban Migration on Child Poverty

Method	**Outcome Variable**	**Caliper/ Strata/ Weight**	**ATT**	**Number of Treated**	**Number of Untreated**
Matching (1)	Child Poverty	-	-0.195^{***} (0.039)	190	190
Matching (2)	Child Poverty	Caliper=0.05	-0.203^{***} (0.042)	177	177
Stratification	Child Poverty	Strata=5	-0.239^{***} (0.035)	190	16,063
Weighting	Child Poverty	Weight=SMR	-0.215^{***} (0.027)	190	16,063

Source: Author's calculations using Zambia LCMS (2015)
Note: Standard errors are reported in parentheses; *, ** and *** denotes statistical significance of 10%, 5%, and 1% respectively.

A remaining issue with the estimates of the ATT is a potential bias because of the post-migration household asset index. The post-migration household asset index leads to biased estimates of the effect of rural-to-urban migration on child poverty if households moved to a different quintile post-migration compared to pre-migration. If households substantially gained assets from migrating and moved to a lower quintile of the asset index (indicating higher wealth), the true effect of rural-to-urban migration would be underestimated as the asset gains were not considered. To the contrary, if households have substantially lost assets from migrating and moved to a higher quintile of the asset index (indicating lower wealth), the true effect would be overestimated as the asset losses would not be accounted for. Even though extreme jumps between several quintiles are unrealistic, it is likely that some households move to a neighboring quintile of the asset index. Therefore, the estimate of the causal effect is likely to be slightly biased. However, this bias can be addressed by analyzing the reported subjective well-being of the household. 37% of all children who migrated from a rural to an urban area come from a household perceived to be better off, 42% perceived to be the same, and 20% perceived to be worse off compared to 12 months ago. This suggests that whereas most households are perceived to remain the same, more households are perceived to be better off than worse off, leading to small perceived welfare improvements on average. This information is crucial to assess the direction of bias. Besides the households that remain in the same quintile of the asset index post-migration, it is most likely that more households move to a lower quintile than to a higher quintile of the asset index. As these welfare improvements are not accounted for in the estimations, the causal effect of rural-to-urban migration is slightly underestimated and does not capture the entire positive impact of migration on child poverty. Based on this, the true absolute ATT is likely higher than 0.2, suggesting an even higher decrease in the probability of migrating children to be multidimensionally poor.

How effective the four methods are in overcoming confounding factors is examined by reassessing the balance of the covariates after the PSM analysis. Whereas the first four columns of *Table 4* display the standardized differences of the confounders after applying the log propensity score, the right column displays the initial standardized differences. *Tables A.17*, *A.18*, *A.19*, and *A.20* in the appendix contain detailed information of the reassessed balances for all four methods. All four methods of estimating the causal effect significantly reduce the standardized differences of the confounding factors between treatment and control group compared to the initial standardized differences.

However, the question remains if they sufficiently remove potential confounding. There exists no consensus on a clear maximum for the standardized difference to tell if the bias is sufficiently eliminated. Proposed maximum absolute standardized differences are in the range of 0.1 to 0.25

(Austin, 2009; Lunt, 2014; Stuart, Lee & Leacy, 2013). Moreover, it is more important to have small standardized differences for theoretically important confounding factors than in less important ones (Garrido et al., 2014). The standardized differences for all observable confounding factors for stratification and weighting are below an absolute value of 0.1, indicating well-balanced covariates. For the two matching processes, 15 respectively 16 of the 19 covariates are below an absolute standardized difference of 0.1. The absolute standardized differences remain above 0.1 for a few covariates. However, most of them are close to 0.1 as only one exceeds 0.15 slightly. Moreover, the confounding factors which remain slightly above 0.1 are those that are expected to be less important than other confounders such as the years of education of the household head or the household asset index. Therefore, both matching processes balance the covariates sufficiently.

Table 4: Reassessing the Balance Between Confounders

	Standardized Differences				
Confounding Factors	Matching (1)	Matching (2)	Stratification	Weighting	Initial Stand. Diff.
Child gender	0.011	-0.011	-0.010	0.002	-0.132
Child age	0.007	-0.016	0.053	0.019	0.112
HH gender	0.051	0.014	-0.049	0.019	-0.047
HH age	-0.072	-0.091	-0.053	0.002	-0.378
HH age^2	-0.095	-0.109	-0.045	-0.001	-0.341
HH married	0.064	0.029	-0.055	0.021	-0.080
HH years of education	0.031	0.018	0.098	0.019	0.670
No. of household members	0.031	0.038	-0.061	-0.003	-0.346
Household asset index	-0.083	-0.064	0.090	-0.028	-0.895
Central	0.167	0.135	-0.027	0.012	-0.055
Copperbelt	-0.000	0.000	-0.012	0.001	-0.135
Eastern	0.020	-0.000	-0.017	0.005	-0.136
Luapula	0.044	0.047	0.018	-0.002	0.164
Lusaka	0.020	0.042	-0.010	-0.012	0.005
Muchinga	-0.035	-0.037	-0.003	-0.009	0.018
Northern	-0.145	-0.131	0.052	0.004	0.207
North-Western	-0.059	-0.063	-0.021	-0.015	0.124
Southern	0.104	0.108	-0.036	0.005	-0.370
Western	0.017	0.018	0.041	0.011	0.056

Source: Author's calculations using Zambia LCMS (2015)

7. Discussion of the Results

The goal of the following section is to firstly connect the presented findings about the determinants and the causal effect of rural-to-urban migration on child poverty to the literature and to afterwards discuss any potential policy implications and limitations of this analysis.

7.1. Determinants of Multidimensional Child Poverty in Zambia

Multidimensional child poverty in Zambia remains relatively high, with 38% of all children being deprived in at least three out of six dimensions. In the context of this dissertation, the determinant of residing in rural areas is the most important one. The consensus of existing literature is that living in rural areas significantly increases the risk of being poor for children (Belete, 2022; Fonta et al., 2020; Lekobane & Roelen, 2020; UNICEF, 2018; National Bureau of Statistics (NBS) and United Nations Children's Fund (UNICEF), 2018). The analysis of this dissertation confirms this finding for the case of Zambia, with living in rural areas being one of the strongest predictors of child poverty.

The findings regarding child characteristics are in line with existing literature, which agrees that older children are less likely to be poor than younger children (Fonta, Yameogo, Tinto, Van Huysen, Natama, Compaore & Fonta, 2020; Lekobane & Roelen, 2020; Ministry of National Development Planning, 2018). This is also the case for children in Zambia. However, this finding does partly depend on the chosen dimensions and indicators per age group, with the youngest age group being identified by two different dimensions than the older two age groups. The evidence regarding the impact of the gender is ambiguous. Whereas Fonta et al. (2020) and UNICEF (2018) find no significant difference between the genders, our findings suggest that boys are slightly more likely to be poor, which is in line with Ferrone and De Milliano (2018).

As for the impact of the gender of the child, the evidence for the impact of the gender of the household head is mixed. Again, our finding is in line with Ferrone and De Milliano (2018), who find the gender to be insignificant in Malawi and Tanzania.

Regarding the household head's age, the results align with Lekobane and Roelen (2020), suggesting that having a young household head increases the probability of being poor. Additionally, I find an increased probability if a child has an old household head, which has been found insignificant by Lekobane and Roelen (2020) and Fonta et al. (2020). One channel through which the age of the household head potentially impacts the probability of being poor for children is income. That children with relatively young (35 years or younger) or old (older than 65 years) household heads are more likely to be poor implies that the income of young and old household heads might be lower than that of household heads aged 36 to 65 years. A similar hump-shaped curve has been shown in the context of the Netherlands, where the income was estimated to increase by 150% between the ages 21 and 45, and to decrease between age 50 and 80 by 50% (Alessie & De Ree, 2009). This indicates that the group of 36 to 65 years old household heads is likely to have the highest income, and therefore more resources to spend on the child.

The evidence on the impact of the marital status of the household head is contradictory. Whereas some researchers suggest that being married decreases the probability of a child of being poor (Lekobane & Roelen, 2020), others argue that divorce decreases the probability (Makhalima, 2020). Ferrone and De Milliano (2018) find a different impact of marital status on child poverty depending on the country analyzed. In Zambia, marital status is not a significant determinant of child poverty, which aligns with the results of Ferrone and De Milliano (2018) for Mali.

Even though not everyone agrees, the great majority of the literature finds the educational level of the household head and the mother to be important determinants of child poverty (Lekobane & Roelen, 2020; Ministry of National Development Planning, 2018; National Bureau of Statistics (NBS) and United Nations Children's Fund (UNICEF), 2016; UNICEF, 2018). This is confirmed in our study, which finds that the higher the educational attainment of the household head and mother, the bigger the decrease in the probability of a child being poor.

In line with the literature (Chen & Corak, 2008; Ferrone & De Milliano, 2018; Lekobane & Roelen, 2020; Makhalima, 2020), living with a household head who is in wage employment significantly decreases the probability of being poor compared to living with a household head who is in self-employment. Generally, the returns to self-employment, especially in agriculture, are low. The share of the self-employed in Zambia is significantly larger than the share of income earned by the self-employed. At the same time, only 27% of households report an income from wage employment, which sums to over 50% of the total income. Amongst the poorest households, agricultural self-employed is the most important source of income (International Growth Centre Zambia, 2017). This suggests creating wage employment opportunities, especially in rural areas where agriculture is widespread.

Most previous research suggests that an increase in the number of children in the household increases the risk of a child being poor (Chen & Corak, 2008; De Miliano & Plavgo, 2018; Ministry of National Development Planning, 2018). This holds true for the case of Zambia. One reason is that the household's resources need to be shared between more children, without increasing household income (Chen & Corak, 2008). At the same time, our findings suggest that the probability of a child being poor decreases with increases in the overall household size. Previous evidence is mixed, as some found the opposite relationship (Lekobane & Roelen, 2020; Makhalima, 2020), while others that living in a large household reduces the risk of being poor (Fonta et al., 2020). An explanation for our finding was made by White and Masset (2003) in the context of Vietnam, who argue that a bigger household size can improve welfare due to economies of scale. Economies of scale apply as specific household items can be seen as public goods (cooking stove for instance), where the consumption of one household member does not decrease the consumption of another member.

Summing up, the findings are in line with the literature. Overall, the probability of children being poor in Zambia increases when living in rural areas, being a very young child and male, living in a relatively small household with many children, having a rather young or old household head, a household head and mother with no formal or low levels of education, and a household head who is self-employed. Awareness of these determinants is important to better target policies that aim to eradicate child poverty.

7.2. The Causal Effect of Rural-to-Urban Migration on Multidimensional Child Poverty

Even though the literature agrees that living in rural areas significantly increases the probability of children being poor, less is known about the impact of rural-to-urban migration on child poverty. Previous research has found that rural-to-urban migration leads to positive income growth effects (Nguyen, Raabe & Grote, 2015) through improved employment opportunities (Mukhtar, Zhong, Tian, Razzaq, Naseer & Hina, 2018), and a higher perceived well-being (Atnafu, Oucho & Zeitlyn, 2014). However, it is also acknowledged that rural-to-urban migration increases the pressure on urban infrastructures, thereby contributing to rising poverty levels in urban areas. Similarly, internal migrants are at risk of settling in poorly planned and overcrowded areas (Awumbila, Owusu & Teye, 2014).

The outcome for children is unknown as no study has yet examined the causal impact of rural-to-urban migration on child poverty. Especially in a multidimensional setting, the risk of a negative causal effect exists as migrating to poorly planned areas could reduce access to basic needs, even if household had higher monetary welfare. For older children, migrating could lead to the temporary loss of education, as a new school must first be found. Moreover, rural-to-urban migration could lead to a loss of the social network in the area of origin (Zhang, 2006). At the same time, forming a new social network in the urban environment can be difficult due to a lack of assimilation (Banerjee, 1983).

This dissertation contributes to the research gap by analyzing the effect of rural-to-urban migration on child poverty. Even though the previously mentioned risks exist, rural-to-urban migration in Zambia significantly decreases the probability of children being multidimensionally poor on average. This is in line with the argument made by Friebel, Gallego, and Mendola (2013), that migrating workers tend to care more about their children's well-being than their own health. The analysis of child deprivations for each dimension revealed that differences between the well-being of children in urban compared to rural areas exist especially in the sanitation dimension. Therefore, it is expected that improvements in sanitation facilities are a major contributor to the observed decrease in the probability of children being poor through rural-to-urban migration. Nevertheless, improvements are also likely to occur in most other dimensions considered in the multidimensional child poverty index.

One potential reason for the decrease in the probability of children being poor could be that whereas in other countries rural-to-urban migrants were found to be extremely poor (Atnafu, Oucho & Zeitlyn, 2014), rural-to-urban migrant children come from an above-average socioeconomic background compared to the rest of the rural population in Zambia. One reason for the observed difference in migrants' background characteristics could be that the migration decision is different depending on household composition. Whereas the extremely poor could likely migrate without children, an average higher level of welfare could be demanded to migrate with children. The relatively high socioeconomic background of the rural-to-urban migrants in the context of this study might in turn reduce the risk of ending up in informal settlements, which could be one potential reason for the observed causal effect.

Moreover, improved employment opportunities in urban areas are likely to play a crucial role in decreasing the probability of children being poor. As the data reveals, a significantly higher share of household heads is in wage employment in urban than in rural areas, suggesting better employment opportunities in urban than in rural areas in Zambia. The returns to labor are higher in urban than in rural areas, as the returns for labor in the agricultural sector are generally lower than in other sectors. As a significantly higher share of the population is working in the agricultural sector in rural than in urban areas, the returns to labor are expected to increase with rural-to-urban migration (De Brauw, Mueller & Lee, 2014; Beegle, De Weerdt & Dercon, 2011).

Besides improved employment opportunities, better education opportunities and access to financial markets can be two channels for the observed causal effect. Regarding education in Zambia, Burger (2011) argues for an educational gap between rural and urban Zambia, which is accounted for by differences in resources and in returns to these resources. Furthermore, urban areas in Zambia offer a better access to financial markets. Rural smallholder farmers are still restricted in their access to financial markets and face difficulties regarding loans to fight poverty. Access to financial markets is expected to be better in urban areas, where commercial banks are concentrated (Sebatta, Wamulume & Mwansakilwa, 2014).

7.3. Policy Implications

Above all, this dissertation underlines the need for multidimensional poverty measurements (non-welfarist approach) as complements to the widespread monetary approach (welfarist approach). As the analysis revealed, a non-welfarist approach to poverty enables a better understanding of the structure of poverty and allows policy makers to specifically aim at fighting poverty in certain dimensions. The detailed analysis of the determinants of child poverty sheds light on the characteristics of multidimensionally poor children in Zambia. Complementing the analysis of dimensional deprivations with the analysis of the determinants of child poverty provides the big picture of which children are most vulnerable to suffer from poverty, and in which dimensions they are most likely deprived. In Zambia, especially the very young children who reside in rural areas with either a young or old household head, who has a low level of education and is not in wage employment are at high risk of being impoverished. Policies fighting child poverty must take the differential needs of children at different ages and their characteristics into account. For instance, having a good understanding of the characteristics of the most vulnerable group can improve the selection process for the regular social cash transfer program, which is one of the cornerstones in the fight against poverty in Zambia.

The need to invest in children's wellbeing in rural areas is prevalent. Even though rural-to-urban migration decreases the probability of children being poor, it cannot be the goal to further enhance rural-to-urban migration, because of reasons such as the increasing pressure on urban infrastructures (Awumbila, Owusu & Teye, 2014) and the formation of informal settlements (Fonta et al., 2020; Islam & Azad, 2007; Ullah, 2004). Additionally, rural-to-urban migrants were shown to have an above average socioeconomic background compared to the rural population. Therefore, rural-to-urban migration in Zambia leads to rural communities losing their relatively wealthy members to urban locations. Besides, even though the probability of child poverty decreases from migration, it is not guaranteed that the mental well-being also increases in urban locations, as children could potentially suffer from the loss of social networks.

Investments in urban infrastructure are important, as urbanization is important for overall economic development (Bertinelli & Black, 2004). But besides fostering urban development, policy makers should engage in making rural areas more attractive to the rural population. Creating the chance of higher living standards in rural areas could lead to changing migration patterns by keeping more people in their area of origin, which would in turn contribute positively to the local development. Overall, households residing in rural areas critically depend on investments in supporting local development. Despite the relatively widespread social cash transfer program, future policies could aim to provide the most vulnerable rural communities with sanitation facilities or similar, as this is one of the dimensions in which most children are deprived.

7.4. Limitations

Before concluding, the limitations of this dissertation are addressed. Regarding the multidimensional child poverty index, this dissertation relies on previous work conducted in Zambia (Ministry of National Development Planning, 2018). All dimensions and indicators are weighed equally, thereby not accounting for potential differences in their importance for children. Besides, the available LCMS 2015 data has limited information regarding mother characteristics. Even though the education and employment of the mother was proxied, specific data indicating the characteristics of the biological mother for all children would have been desired. The greatest limitation of this analysis is the unavailability of any monetary welfare measure pre-migration. This led to the inclusion of a household asset ownership index from post-migration in the estimation of the causal effect, which is likely to slightly bias the results. Even though I was able to elaborate on the direction of the bias, having information on monetary household welfare pre-migration would improve the quality of the PSM. Lastly, the data only indicates if an individual migrated in the past 12 months or not. Therefore, the specific time of migration is unknown. Moreover, no information is available if individuals plan to migrate temporarily or permanently.

8. Concluding Remarks

This dissertation analyzed child poverty in Zambia, based on data from the LCMS 2015 VII. In contrast to the widespread welfarist approach to poverty, the analysis is characterized by a non-welfarist approach to poverty by estimating a multidimensional child poverty index. The index consists of six dimensions per age group and takes the different needs of children at different ages into account.

Poverty remains a serious problem in Zambia. In 2015, over 61% of the population lived below a level of 2.15 US dollars per day in 2017 PPP (World Bank, 2023). This dissertation revealed that over 38% of all children are deprived in at least three out of six dimensions and over three-fourths of all children suffer from at least one deprivation. Therefore, policies supporting children in their access to basic needs are essential.

The main objectives of this analysis were twofold. First, the determinants of multidimensional child poverty were analyzed by applying a probit model. This is a significant contribution to the literature, as it enables a better understanding of the characteristics of multidimensionally poor children in Zambia. The estimations revealed that especially young and male children residing in rural areas, with a relatively young or old household head, who has low levels of education and is self-employed are at risk to suffer multidimensional poverty. Additionally, the educational level of the mother, household size, and number of children were found to be significant determinants of child poverty in Zambia. This provides the big picture of the most vulnerable individuals in Zambia and suggests that policies should specifically aim to improve the living conditions for this group.

Secondly, this dissertation went beyond estimating correlations of household characteristics with child poverty. After the analysis of the determinants revealed that living in rural compared to urban areas is one of the strongest predictors of child poverty, this dissertation examined an analysis of the causal effects of rural-to-urban migration on child poverty, which has so far not been done. A PSM analysis was applied using the three different methods of matching, weighting, and stratification. The estimates revealed that rural-to-urban migration significantly reduces the probability of children being multidimensionally poor by an estimated 20 percentage points on average, which are likely to be slightly underestimated. However, well-being improvements are not guaranteed as the risk of migrating into slums or informal settlements persists. Overall, while rural-to-urban migration presents a way out of poverty for children residing in rural areas, it also increases the pressure on urban infrastructures. Therefore, policy makers must aim to enhance the local development of rural areas.

Future research based on more recent data is needed regarding multidimensional poverty in Zambia. This could help to elaborate on recent trends, also in the context of Covid-19. Additionally, research on the causal effects of further strong determinants, such as the education of the household head or mother, is needed for a better understanding of the mechanisms through which these determinants impact child poverty. Lastly, future research should analyze the effectiveness of any potential policies that aim to support children residing in rural households.

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Appendix

Table A.1: Overview of the Dimensions, Indicators, and Deprivation Thresholds

Dimension	Indicator	Deprivation Threshold
Nutrition	Infant and Young Child Feeding: Exclusive Breastfeeding	0-5 months: Child is not exclusively breastfed
	Infant and Young Child Feeding: Meal Frequency	6-59 months: Currently breastfeeding children: 6-8 months: Child has not received a minimum of 2 complementary feedings a day. 9-23 months: Child has not received at least 3 complementary feedings a day. 6-59 months: Currently non-breastfeeding children: Child has not received at least 4 feedings/meals a day.
	Weight for Height (Wasting)	0-59 months: Child's weight-for-height Z-score is below minus two standard deviations (-2 SD) from the median of the WHO reference population, considered acutely malnourished. (Due to data quality, observations which are outside of $\pm$ 3SD $\pm$ 10% margin from the median for height or weight are considered unrealistic and dropped from the sample. This is in line with minimum and maximum values from the 1st and 99th percentile of the distribution. Intervals of 5 cm were considered. An individual within an interval is considered undernourished if it is below -2 SD of the lowest height. I am aware that this is a slight underestimation, as the true value for taller individuals in this interval is higher.)
Health	Full Immunization	0-59 months: Child has not received all basic vaccinations by the recommended date. 0-12 months: Tuberculosis (BCG) 12-59 months: Child has not received a vaccination against BCG, and three doses of each of the following: Diphtheria; Pertussis; Tetanus / Hepatitis /HaemophilusInfluenzae type b (DPT-HepB-Hib). Additionally, they must be vaccinated against Polio (3) and Measles.
Child Protection	Child Marriage	12-17 years: Child is married, cohabiting with the partner, or ever married (married, widowed, divorced).
	Child Labor	5-15 years: Child younger than 15 years of age is engaged in any income generating activity (wage employment, running a business, piecework) or farming, fishing, or an unpaid family worker.
Information	Availability of Information Devices	0-17 years: Household does not have at least one of the following devices: TV, radio, PC, phone, mobile phone.
Education	Compulsory School Attendance	7-13 years: Child of compulsory school age is not currently attending school.
	Grade-for-Age	7-17 years: Child is not attending at school age or attending school but 2 or more years behind the corresponding grade for the age. A problem occurs as children could be 7 or 8 in grade 1, 8 or 9 in grade 2, and so on. Therefore, I either underestimate or overestimate poverty slightly, as I do not know for sure if, for instance, someone aged 9 in grade 1 is

		1 year or 2 years behind schedule. As the usual starting age for primary school in Zambia is 7, I count an individual as deprived if he or she is aged 9 or older in grade 1, 10 or older in grade 2, and so on. This age classification is also in line with the other indicators. However, it leads to a slight overestimation.
	Primary School Attainment	14-17 years: Child beyond primary school age with no or incomplete primary education.
Housing	Overcrowding	0-17 years: Household has on average more than four people per room (excluding bathrooms and toilets)
	Housing Material	0-17 years: Both roof and floor are made of (natural) materials, which are not considered permanent. Floor: mud, wood (not wooden tiles), sand, soil, flat stones, no floor. Roof: no roof, thatch/palm leaf, rustic mat, palm/bamboo, cardboard, mud tiles, glass, grass, plastic paper, sheets of rubber.
Sanitation	Access to Improved Sanitation	0-17 years: Household usually uses unimproved toilet facility: pit latrine without slab or open pit (Own, communal or from another household), no facility, bush or field, bucket or another container, others.
	Garbage Disposal	0-17 years: Household garbage disposal: not refuse collected or pit, but dumped in undesignated places, or burned.
Water	Drinking Water Source	0-17 years: Household main source of drinking water is unimproved. Unimproved water sources: unprotected well, unprotected spring, surface water (directly from river, stream, dam). Also deprived if main source is bottled water and the source of main non-drinking water is unimproved.
	Water Treatment	0-17 years: Unimproved water source is not treated or is not appropriately treated. Appropriate treatment method: boiling, adding bleach or chlorine, using a water filter.

Source: Adapted from Ministry of National Development Planning (2018)

Table A.2: Overview of Variables used for the Analysis of the Determinants

Variable	Explanation
Dependent Variable	
Probability of a child being multidimensionally poor	=1 if a child is deprived in at least 3 out of 6 dimensions, 0 otherwise
Independent Variables	
$\boldsymbol{X_1}$: **Child Characteristics**	
Child gender	=1 if child is male, 0 otherwise
Child aged 0-4 years	=1 if child is aged 0-4 years, 0 otherwise
Child aged 5-13 years	=1 if child is aged 5-13 years, 0 otherwise
Child aged 14-17 years	=1 if child is aged 14-17 years, 0 otherwise
$\boldsymbol{X_2}$: **Household Head (HH) Characteristics**	
HH gender	=1 if HH is male; 0 otherwise
HH aged 35 years or younger	=1 if HH is aged less than 35 years; 0 otherwise
HH aged 36-65 years	=1 if HH is aged 36-65 years; 0 otherwise
HH aged older than 65 years	=1 if HH is older than 65 years; 0 otherwise
HH is married	=1 if HH is married; 0 otherwise
HH is never married	=1 if HH is never married; 0 otherwise
HH is separated	=1 if HH is separated; 0 otherwise
HH is divorced	=1 if HH is divorced; 0 otherwise
HH is widowed	=1 if HH is widowed; 0 otherwise
HH is cohabitating	=1 if HH is cohabitating; 0 otherwise
HH no formal education	=1 if HH has not received formal schooling; 0 otherwise
HH primary schooling	=1 if HH attained min. grade 1, max. grade 7; 0 otherwise
HH secondary schooling	=1 if HH attained min. grade 8, max. grade 12; 0 otherwise
HH tertiary schooling	=1 if HH has diploma, bachelor's/ master's/ doctorate degree; 0 otherwise
HH in wage-employment	=1 if HH is in wage-employment; 0 if in self-employment
$\boldsymbol{X_3}$: **Mother Characteristics**	
Mother no formal education	=1 if mother has not received formal schooling; 0 otherwise
Mother primary schooling	=1 if mother attained min. grade 1, max. grade 7; 0 otherwise
Mother secondary schooling	=1 if mother attained min. grade 8, max. grade 12; 0 otherwise
Mother tertiary schooling	=1 if mother has diploma, bachelor's/ master's/ doctorate degree; 0 otherwise
Mother in wage-employment	=1 if mother is in wage-employment; 0 otherwise
Mother in self-employment	=1 if mother is in self-employment; 0 otherwise
Mother is an unpaid family worker	=1 if mother is an unpaid family worker; 0 otherwise
$\boldsymbol{X_4}$: **Household Composition**	
Number of household members	Total number of household members (continuous variable)
Number of children in the household	Total number of children in the household (continuous var.)
$\boldsymbol{X_5}$: **Geographic Characteristics**	
Residing in an urban location	=1 if a child is residing in an urban location; 0 otherwise
Provinces 1-10 (10 dummy variables)	=1 if residing in a given province; 0 otherwise

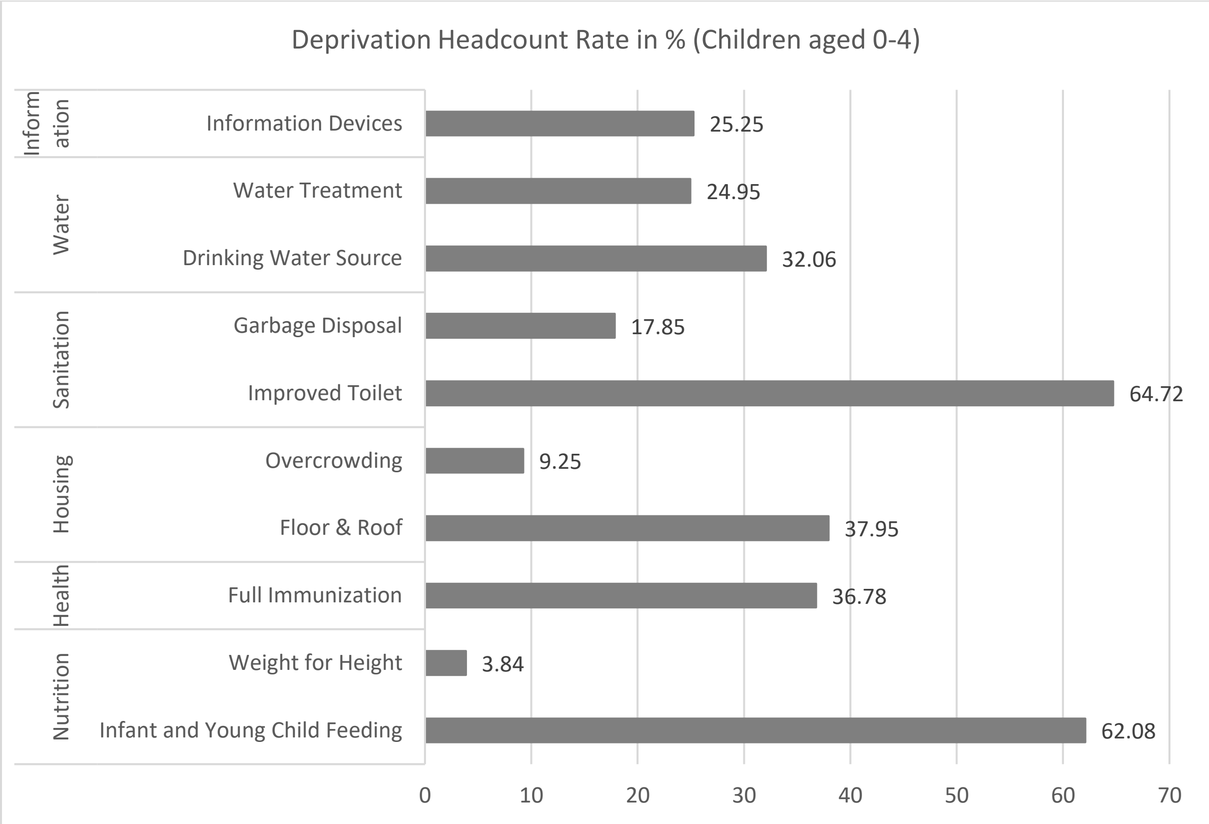
Table A.3: Overview of the Items Included in the Household Asset Index

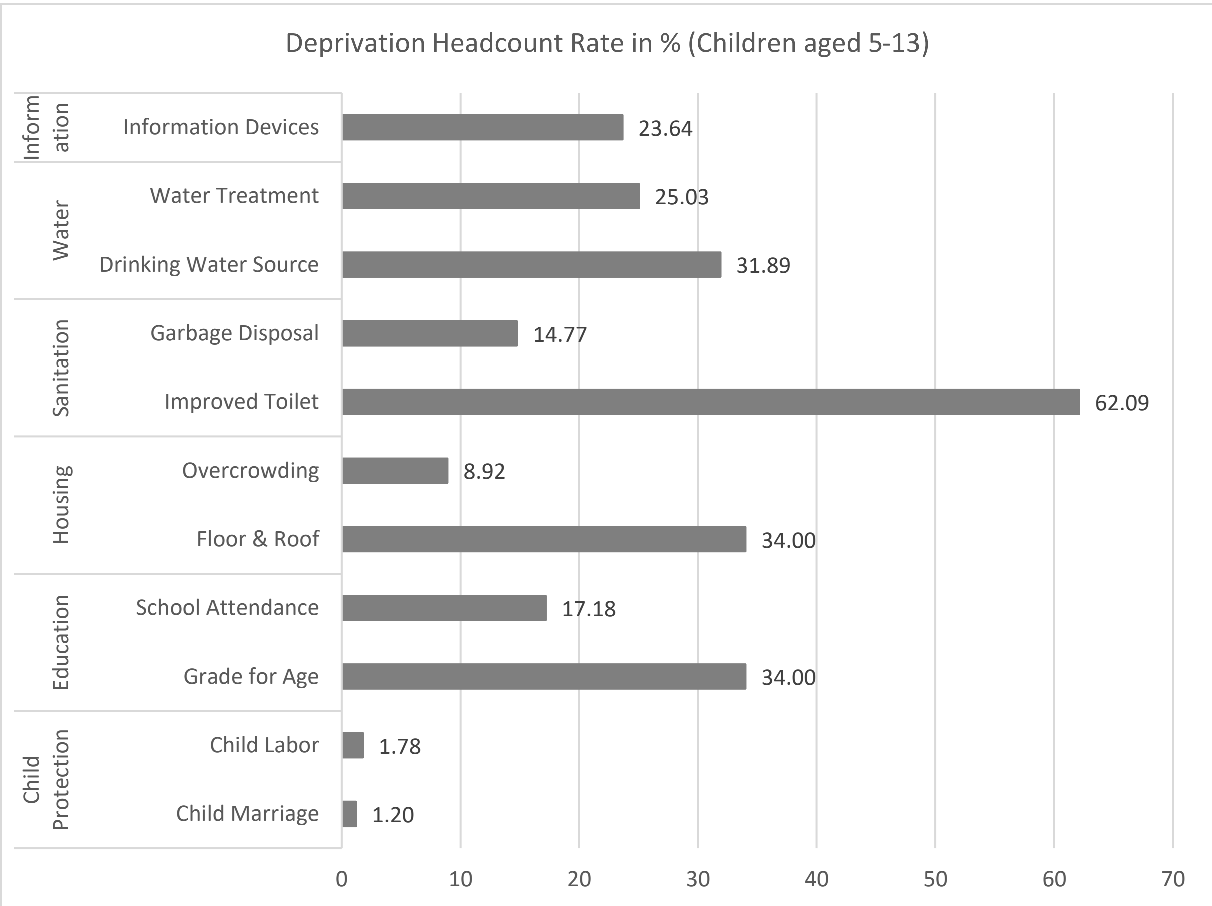
General Items	Kitchen/Household	Tools & Machines	Transport	Animals
• Bed • Mattress • Mosquito net • Table (dining) • Lounge suit/sofa • Radio/Stereo • Television • Satellite dish/ decoder (free air) • Satellite dish/ decoder (DSTV) • Other pay TV • DVD/VCR • Home theater • Land phone • Cellular phone • Computer • Watch • Clock	• Residential building • Non-resid. building • Brazier/Mbaula • Gas stove • Electric stove • Refrigerator • Deep freezer • Washing machine • Dish washer • Air conditioner • Electric iron • Non-electric iron • Private water pump	• Sewing machine • Hand hammer mill • Grinding/hammer mill • Sheller • Ramp presses/ oil expellers • Hand saw • Carpentry plane • Axe • Pick • Hoe • Hammer • Shovel/spade • Fishing net • Hunting gun • Plough • Crop sprayer • Knitting machine • Lawn mowers • Generator	• Small/hand-driven tractor • 4-wheel tractor • Wheelbarrow • Scotch cart • Bicycle • Motorcycle • Large truck • Small/pick-up truck • Van/minibus • Car • Canoe • Boat	• Oxen • Donkeys

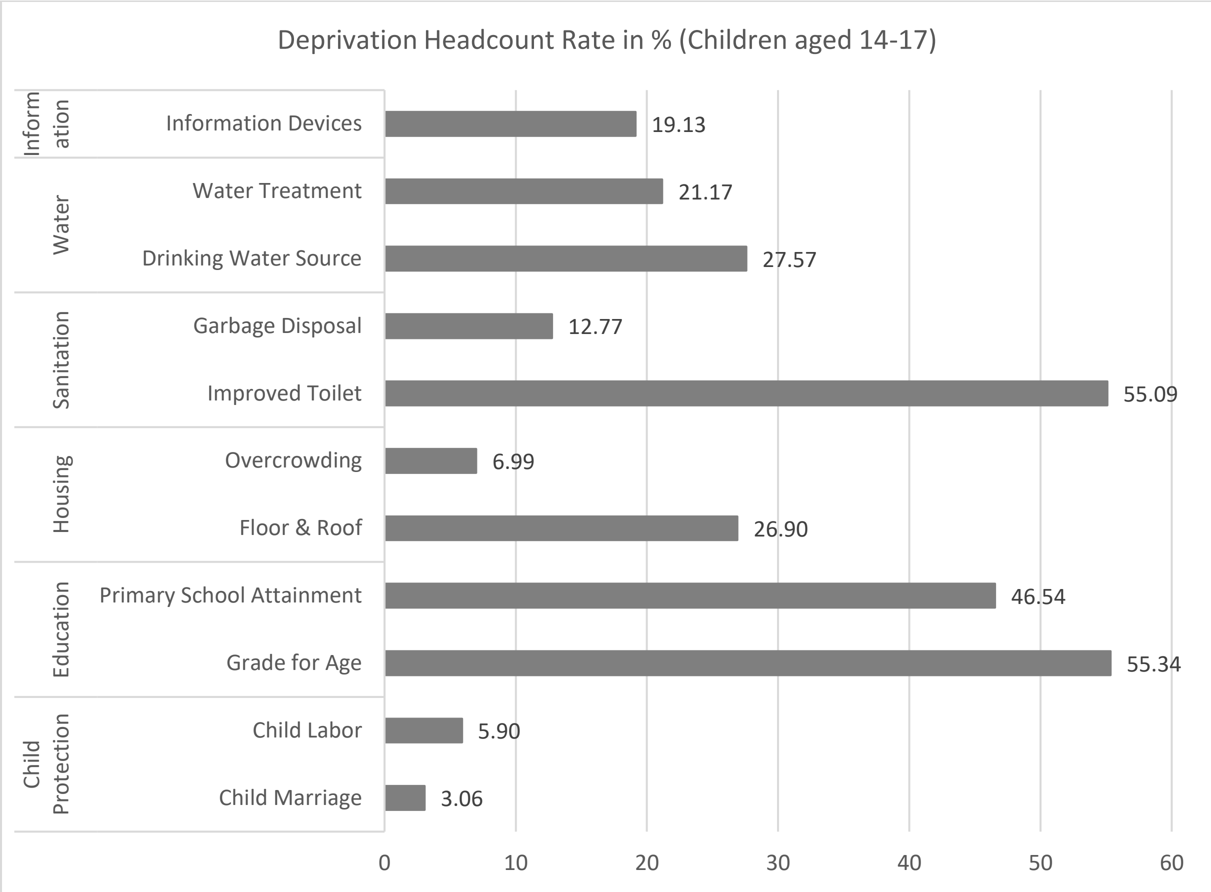
Table A.4: Overview of Variables Used for PSM

Variable	Explanation
Outcome Variable	
Probability of a child being multidimensionally poor	=1 if a child is deprived in at least 3 out of 6 dimensions, 0 otherwise
Treatment Variable	
Rural-to-urban migration	=1 if a child migrated from a rural to an urban location within Zambia in the past 12 months; 0 otherwise
Independent Variables	
X_1: **Child Characteristics**	
Child gender	=1 if child is male, 0 otherwise
Child age	Age of the child in years (continuous variable)
X_2: **Household Head (HH) Characteristics**	
HH gender	=1 if HH is male; 0 otherwise
HH age	Age of the HH in years (continuous variable)
HH age squared	Squared age of the HH in years (continuous variable)
HH is married	=1 if HH is married; 0 otherwise
HH years of schooling	Years of schooling of the HH (continuous variable)
X_3: **Household Welfare**	
Household asset ownership index	The index is split into 5 quintiles. A value of 1 represents the quintile with the wealthiest households and 5 with the poorest households
X_4: **Household Composition and Location**	
Number of household members	Total number of household members (continuous variable)
Provinces 1-10 (10 dummy variables)	=1 if residing in a given province; 0 otherwise

Figure A.1: Detailed Analysis of Deprivations of Each Indicator of Each Age Group







Source: Author's calculations using Zambia LCMS (2015)

Table A.5: Descriptive Statistics

Variable	N	Mean	SD	Min	Max
Dependent Variable					
Multidimensional child poverty	18,127	0.4451	0.4970	0	1
Independent Variables					
Child Characteristics					
Child gender	18,127	0.4863	0.4998	0	1
Child aged 0-4 years	18,127	0.1269	0.3329	0	1
Child aged 5-13 years	18,127	0.6152	0.4866	0	1
Child aged 14-17 years	18,127	0.2341	0.4234	0	1
Household Head (HH) Characteristics					
HH gender	18,127	0.7241	0.4470	0	1
HH aged 35 years or younger	18,127	0.2546	0.4356	0	1
HH aged 36-65 years	18,127	0.6902	0.4624	0	1
HH aged older than 65 years	18,127	0.0551	0.2282	0	1
HH is married	18,127	0.7602	0.4269	0	1
HH is never married	18,127	0.0209	0.1429	0	1
HH is separated	18,127	0.0287	0.1671	0	1
HH is divorced	18,127	0.0691	0.2537	0	1
HH is widowed	18,127	0.1201	0.3251	0	1
HH is cohabitating	18,127	0.0009	0.0306	0	1
HH no formal education	18,127	0.0812	0.2732	0	1
HH primary schooling	18,127	0.4472	0.4972	0	1
HH secondary schooling	18,127	0.3841	0.4864	0	1
HH tertiary schooling	18,127	0.0874	0.2825	0	1
HH in wage-employment	18,127	0.2184	0.4132	0	1
Mother Characteristics					
Mother no formal education	18,127	0.1283	0.3344	0	1
Mother primary schooling	18,127	0.5300	0.4991	0	1
Mother secondary schooling	18,127	0.2863	0.4520	0	1
Mother tertiary schooling	18,127	0.0555	0.2290	0	1
Mother in wage-employment	18,127	0.1376	0.3445	0	1
Mother in self-employment	18,127	0.6160	0.4864	0	1
Mother is an unpaid family worker	18,127	0.2453	0.4303	0	1
Household Composition					
Number of household members	18,127	7.0188	2.9175	2	29
Number of children in the household	18,127	4.1098	2.1285	1	23
Geographic Characteristics					
Residing in an urban location	18,127	0.3346	0.4719	0	1
Provinces 1-10 (10 dummy variables)	18,127	≈0.1	≈0.3	0	1

Source: Author's calculations using Zambia LCMS (2015)
Note: N=Number of observations; SD=Standard Deviation; Min=Minimum; Max=Maximum

Table A.6: Information Criteria of the Logit Model

Model	Obs	11(null)	11(model)	df	AIC	BIC
Logit	18,127	-12455.34	-8256.04	33	16578.09	16835.66
Note: N=Obs. used in calculating BIC						

Source: Author's calculations using Zambia LCMS (2015)

Table A.7: Information Criteria of the Probit Model

Model	Obs	11(null)	11(model)	df	AIC	BIC
Probit	18,127	-12455.34	-8251.14	33	16568.28	16825.85
Note: N=Obs. used in calculating BIC						

Source: Author's calculations using Zambia LCMS (2015)

Table A.8: Marginal Effects at Means of the Probit Model

	Dependent Variable: Multidimensional child poverty
Independent Variables	Marginal Effects at Means
Child gender	0.024^{***} (0.008)
Child aged 5-13 years	-0.254^{***} (0.012)
Child aged 14-17 years	-0.133^{***} (0.014)
HH gender	-0.005 (0.022)
HH aged 35 years or younger	0.056^{***} (0.011)
HH aged older than 65 years	0.042^{**} (0.018)
HH is never married	0.037 (0.039)
HH is separated	0.053 (0.033)
HH is divorced	0.034 (0.027)
HH is widowed	0.021 (0.024)
HH is cohabitating	0.189 (0.182)
HH primary schooling	-0.068^{***} (0.018)
HH secondary schooling	-0.190^{***} (0.020)
HH tertiary schooling	-0.483^{***} (0.045)
HH in wage-employment	-0.166^{***} (0.017)
Mother primary schooling	-0.089^{***} (0.015)
Mother secondary schooling	-0.252^{***}

	(0.018)
Mother tertiary schooling	-0.575***
	(0.082)
Mother in wage-employment	-0.015
	(0.022)
Mother is an unpaid family worker	0.013
	(0.011)
Number of household members	-0.033***
	(0.003)
Number of children in the household	0.030***
	(0.004)
Residing in an urban location	-0.404***
	(0.011)
Central	-0.352***
	(0.020)
Copperbelt	-0.366***
	(0.021)
Eastern	-0.401***
	(0.019)
Luapula	-0.071***
	(0.019)
Lusaka	-0.554***
	(0.024)
Muchinga	-0.118***
	(0.020)
Northern	-0.028
	(0.020)
North-Western	-0.227***
	(0.020)
Southern	-0.329***
	(0.019)
Observations	18,127

Source: Author's calculations using Zambia LCMS (2015)
Note: Standard errors are reported in parentheses; *, ** and *** denotes statistical significance of 10%, 5%, and 1% respectively.

Table A.9: Robustness Check of the Marital Status of HH Excluding Mother Characteristics. Probit Estimation

	Dependent Variable: Multidimensional child poverty	
Independent Variables	Coefficients	Average Marginal Effects
Child gender	0.050^{***}	0.012^{***}
	(0.019)	(0.005)
Child aged 5-13 years	-0.701^{***}	-0.171^{***}
	(0.027)	(0.006)
Child aged 14-17 years	-0.372^{***}	-0.091^{***}
	(0.032)	(0.008)
HH gender	0.002	0.000
	(0.047)	(0.011)
HH aged 35 years or younger	0.095^{***}	0.023^{***}
	(0.024)	(0.006)
HH aged older than 65 years	0.120^{***}	0.029^{***}
	(0.043)	(0.010)
HH is never married	0.068	0.017
	(0.087)	(0.021)
HH is separated	0.083	0.020
	(0.072)	(0.018)
HH is divorced	0.099	0.024
	(0.061)	(0.015)
HH is widowed	0.033	0.008
	(0.055)	(0.013)
HH is cohabitating	0.788^{*}	0.192^{*}
	(0.413)	(0.101)
HH primary schooling	-0.321^{***}	-0.078^{***}
	(0.036)	(0.009)
HH secondary schooling	-0.836^{***}	-0.204^{***}
	(0.037)	(0.009)
HH tertiary schooling	-2.118^{***}	-0.516^{***}
	(0.091)	(0.022)
HH in wage-employment	-0.446^{***}	-0.109^{***}
	(0.028)	(0.007)
Number of household members	-0.100^{***}	-0.024^{***}
	(0.008)	(0.002)
Number of children in the household	0.098^{***}	0.024^{***}
	(0.010)	(0.002)
Residing in an urban location	-1.216^{***}	-0.296^{***}
	(0.024)	(0.005)
Central	-0.950^{***}	-0.232^{***}
	(0.044)	(0.010)
Copperbelt	-0.888^{***}	-0.217^{***}
	(0.045)	(0.011)
Eastern	-0.945^{***}	-0.230^{***}
	(0.042)	(0.010)
Luapula	-0.113^{***}	-0.028^{***}
	(0.043)	(0.010)
Lusaka	-1.387^{***}	-0.338^{***}
	(0.050)	(0.012)
Muchinga	-0.269^{***}	-0.066^{***}
	(0.044)	(0.011)
Northern	-0.053	-0.013
	(0.043)	(0.011)
North-Western	-0.499^{***}	-0.122^{***}

	(0.043)	(0.010)
Southern	-0.866***	-0.211***
	(0.042)	(0.010)
Constant	2.131***	
	(0.075)	
Observations	26,812	26,812

Source: Author's calculations using Zambia LCMS (2015)
Note: Standard errors are reported in parentheses; *, ** and *** denotes statistical significance of 10%, 5%, and 1% respectively.

Table A.10: Classification

	True		
Classified	D	~D	Total
+	6236	2269	8505
-	1833	7789	9622
Total	8069	10058	18127

Classified + if predicted Pr(D) >=0.5
True D defined as multidimensional child poverty !=0

Sensitivity	Pr (+ | D)	77.28%
Specificity	Pr (- | ~D)	77.44%
Positive predictive value	Pr (D | +)	73.32%
Negative predictive value	Pr (~D | -)	80.95%
False + rate for true ~D	Pr (+ | ~D)	22.56%
False - rate for true D	Pr (- | D)	22.72%
False + rate for classified +	Pr (~D | +)	26.68%
False - rate for classified -	Pr (D | -)	19.05%
Correctly classified		**77.37%**

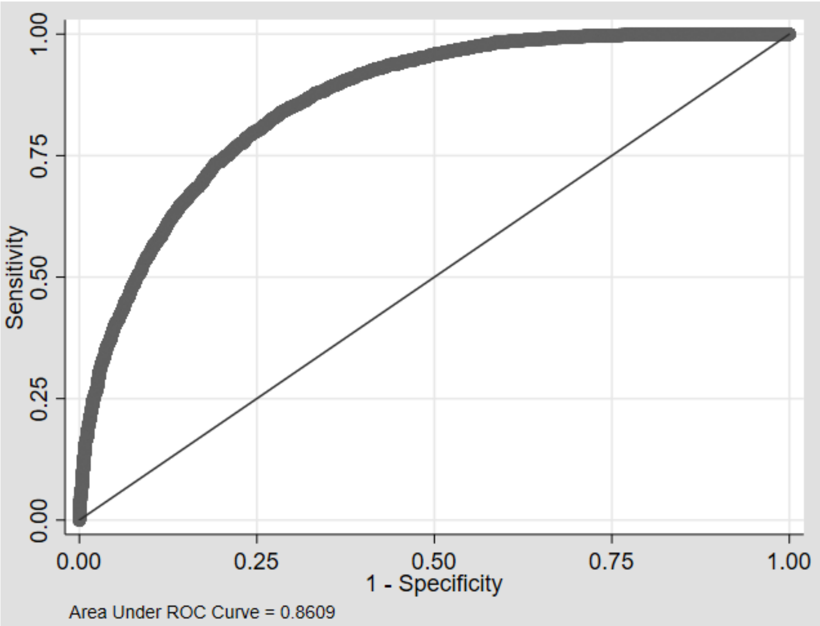
Source: Author's calculations using Zambia LCMS (2015)

Table A.11: Link Test

	Dependent Variable: Multidimensional child poverty
Independent Variables	Coefficients
_hat	1.005***
	(0.015)
_hatsq	0.012
	(0.013)
_cons	-0.008
	(0.014)
Observations	18,127

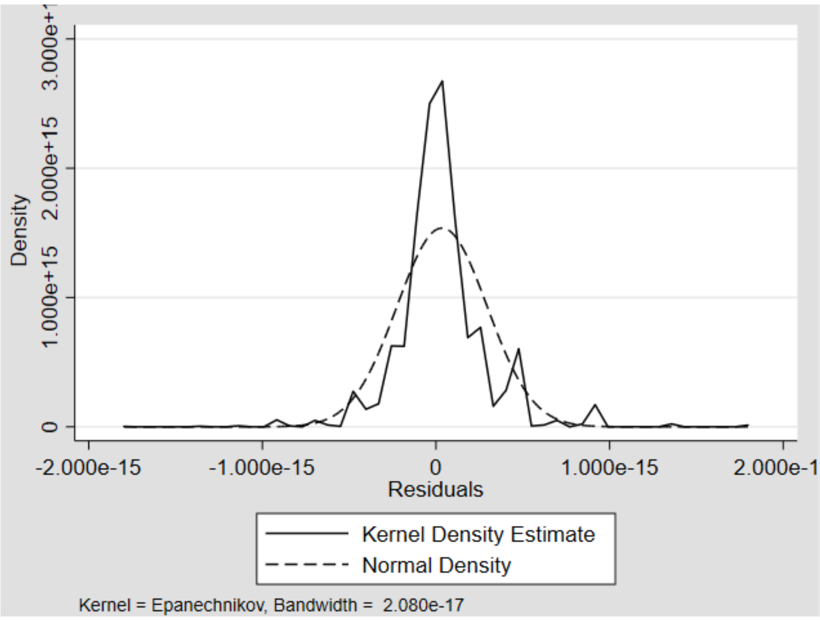
Source: Author's calculations using Zambia LCMS (2015)
Note: Standard errors are reported in parentheses; *, ** and *** denotes statistical significance of 10%, 5%, and 1% respectively.

Figure A.2: ROC Curve



Source: Author's calculations using Zambia LCMS (2015)

Figure A.3: Kernel Density Estimate



Source: Author's calculations using Zambia LCMS (2015)

Table A.12: Information Criteria of the Logit Model

Model	Obs	11(null)	11(model)	df	AIC	BIC
Logit	16,253	-1034.20	-848.71	19	1735.43	1881.65
			Note: N=Obs used in calculating BIC			

Source: Author's calculations using Zambia LCMS (2015)

Table A.13: Information Criteria of the Probit Model

Model	Obs	11(null)	11(model)	df	AIC	BIC
Probit	16,253	-1034.20	-854.33	19	1746.66	1892.88
	Note: N=Obs used in calculating BIC					

Source: Author's calculations using Zambia LCMS (2015)

Table A.14: Logit Estimation for PSM

Independent Variables	Dependent Variable: Rural-to-urban migration Coefficients
Child gender	-0.201 (0.152)
Child age	0.022 (0.017)
HH gender	-0.227 (0.355)
HH age	-0.123*** (0.039)
HH age squared	0.001** (0.000)
HH is married	-0.341 (0.364)
HH years of schooling	0.025 (0.025)
Number of household members	-0.160*** (0.037)
Household asset ownership index	-1.077*** (0.085)
Central	-1.042*** (0.339)
Copperbelt	-1.294*** (0.412)
Eastern	-0.674* (0.352)
Luapula	0.561* (0.301)
Lusaka	-1.588*** (0.359)
Muchinga	-0.481 (0.336)
Northern	0.415 (0.297)
North-Western	0.078 (0.304)
Southern	-1.821*** (0.472)
Constant	4.108*** (0.992)
Observations	16,253

Source: Author's calculations using Zambia LCMS (2015)
Note: Standard errors are reported in parentheses; *, ** and *** denotes statistical significance of 10%, 5%, and 1% respectively.

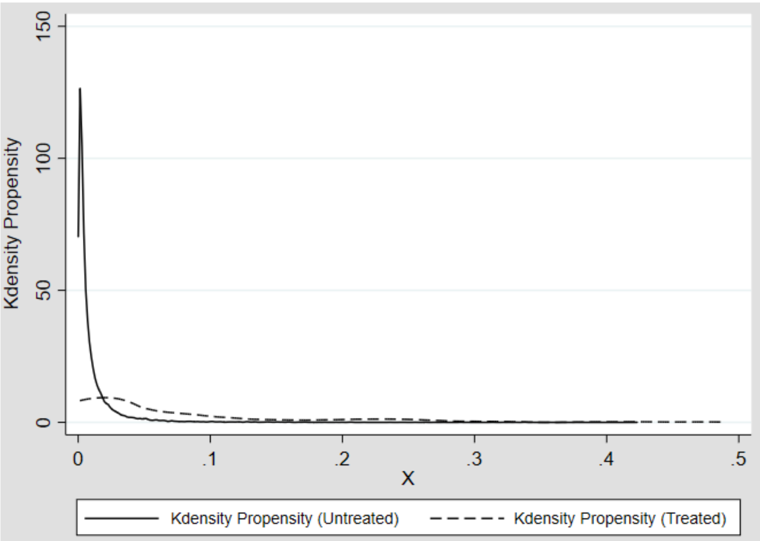
Table A.15: Hosmer-Lemeshow Test

Group	Prob	Obs_1	Exp_1	Obs_0	Exp_0	Total
1	0.0008	0	0.8	1626	1625.2	1626
2	0.0015	2	1.8	1623	1623.2	1625
3	0.0022	6	3.0	1619	1622.0	1625
4	0.0031	7	4.3	1619	1621.7	1626
5	0.0044	8	6.1	1617	1618.9	1625
6	0.0063	7	8.6	1618	1616.4	1625
7	0.0092	16	12.3	1610	1613.7	1626
8	0.0143	14	18.6	1611	1606.4	1625
9	0.0259	29	31.0	1596	1594.0	1625
10	0.4874	101	103.6	1524	1521.4	1625

Number of observations	= 16,253
Number of groups	= 10
Hosmer-Lemeshow chi2(8)	= 8.80
Prob > chi2	= 0.3594

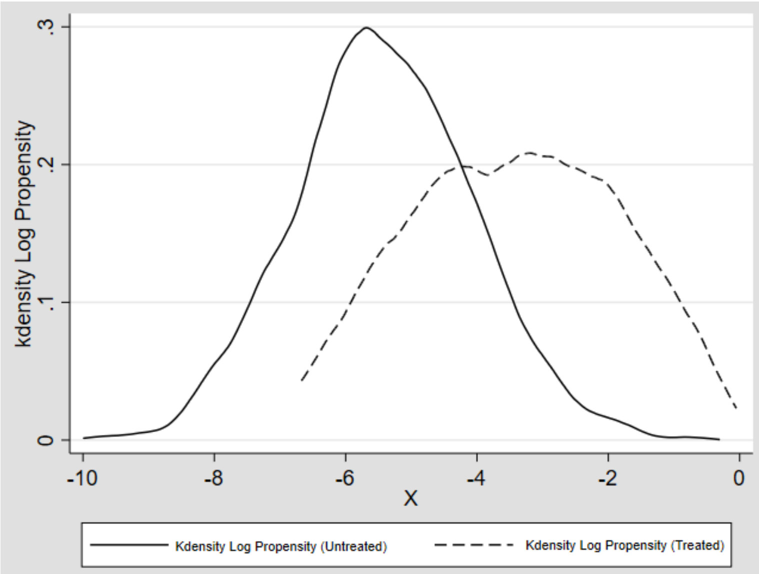
Source: Author's calculations using Zambia LCMS (2015)

Figure A.4: Distribution of the Propensity Score



Source: Author's calculations using Zambia LCMS (2015)

Figure A.5: Distribution of the Log Propensity Score



Source: Author's calculations using Zambia LCMS (2015)

Table A.16: Balance of Confounders

Confounding Factors	Mean in Treated	Mean in Untreated	Standardized Differences
Child gender	0.43	0.49	-0.132
Child age	9.77	9.24	0.112
HH gender	0.79	0.81	-0.047
HH age	39.47	44.04	-0.378
HH age^2	1690.56	2096.84	-0.341
HH married	0.80	0.83	-0.080
HH years of education	9.10	6.57	0.670
Number of household members	6.22	7.12	-0.346
Household asset index	2.68	3.82	-0.895
Central	0.09	0.11	-0.055
Copperbelt	0.05	0.08	-0.135
Eastern	0.08	0.12	-0.136
Luapula	0.16	0.10	0.164
Lusaka	0.08	0.08	0.005
Muchinga	0.09	0.09	0.018
Northern	0.17	0.10	0.207
North-Western	0.14	0.10	0.124
Southern	0.03	0.13	-0.370
Western	0.12	0.10	0.056

Source: Author's calculations using Zambia LCMS (2015)

Table A.17: Reassessing the Balance Between Confounders - Matching (1)

Confounding Factors	Mean in Treated	Mean in Untreated	Standardized Differences
Child gender	0.43	0.42	0.011
Child age	9.77	9.74	0.007
HH gender	0.79	0.77	0.051
HH age	39.47	40.37	-0.072
HH age^2	1690.56	1802.91	-0.095
HH married	0.80	0.77	0.064
HH years of education	9.10	8.98	0.031
Number of household members	6.22	6.15	0.031
Household asset index	2.68	2.79	-0.083
Central	0.09	0.05	0.167
Copperbelt	0.05	0.05	-0.000
Eastern	0.08	0.07	0.020
Luapula	0.16	0.14	0.044
Lusaka	0.08	0.07	0.020
Muchinga	0.09	0.11	-0.035
Northern	0.17	0.23	-0.145
North-Western	0.14	0.16	-0.059
Southern	0.03	0.02	0.104
Western	0.12	0.11	0.017

Source: Author's calculations using Zambia LCMS (2015)

Table A.18: Reassessing the Balance Between Confounders - Matching (2)

Confounding Factors	Mean in Treated	Mean in Untreated	Standardized Differences
Child gender	0.42	0.43	-0.011
Child age	9.49	9.56	-0.016
HH gender	0.80	0.80	0.014
HH age	39.84	40.97	-0.091
HH age^2	1721.07	1851.50	-0.109
HH married	0.81	0.80	0.029
HH years of education	8.74	8.67	0.018
Number of household members	6.34	6.25	0.038
Household asset index	2.79	2.88	-0.064
Central	0.08	0.05	0.135
Copperbelt	0.05	0.05	0.000
Eastern	0.08	0.08	-0.000
Luapula	0.16	0.15	0.047
Lusaka	0.08	0.07	0.042

Muchinga	0.10	0.11	-0.037
Northern	0.16	0.21	-0.131
North-Western	0.14	0.16	-0.063
Southern	0.03	0.02	0.108
Western	0.11	0.10	0.018

Source: Author's calculations using Zambia LCMS (2015)

Table A.19: Reassessing the Balance Between Confounders - Stratification

Confounding Factors	Mean in Treated	Mean in Untreated	Standardized Differences
Child gender	0.43	0.43	-0.010
Child age	9.77	9.52	0.053
HH gender	0.79	0.81	-0.049
HH age	39.47	40.11	-0.053
HH age^2	1690.56	1743.66	-0.045
HH married	0.80	0.82	-0.055
HH years of education	9.10	8.73	0.098
Number of household members	6.22	6.38	-0.061
Household asset index	2.68	2.80	0.090
Central	0.09	0.10	-0.027
Copperbelt	0.05	0.05	-0.012
Eastern	0.08	0.08	-0.017
Luapula	0.16	0.15	0.018
Lusaka	0.08	0.08	-0.010
Muchinga	0.09	0.10	-0.003
Northern	0.17	0.15	0.052
North-Western	0.14	0.14	-0.021
Southern	0.03	0.04	-0.036
Western	0.12	0.10	0.041

Source: Author's calculations using Zambia LCMS (2015)

Table A.20: Reassessing the Balance Between Confounders - Weighting

Confounding Factors	Mean in Treated	Mean in Untreated	Standardized Differences
Child gender	0.43	0.43	0.002
Child age	9.77	9.68	0.019
HH gender	0.79	0.78	0.019
HH age	39.47	39.45	0.002
HH age^2	1690.56	1691.22	-0.001
HH married	0.80	0.79	0.021
HH years of education	9.10	9.03	0.019
Number of household members	6.22	6.22	-0.003
Household asset index	2.68	2.72	-0.028
Central	0.09	0.09	0.012
Copperbelt	0.05	0.05	0.001
Eastern	0.08	0.08	0.005
Luapula	0.16	0.16	-0.002
Lusaka	0.08	0.08	-0.012
Muchinga	0.09	0.10	-0.009
Northern	0.17	0.17	0.004
North-Western	0.14	0.14	-0.015
Southern	0.03	0.03	0.005
Western	0.12	0.11	0.011

Source: Author's calculations using Zambia LCMS (2015)