ESTIMATING MULTIDIMENSIONAL POVERTY INDEX AND ITS GROWTH TRAJECTORIES USING SEM: A CASE STUDY OF PAKISTAN

By

Umair Khan

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Supervisor

Dr. Ahsan ul Haq

PIDE School of Economics
Pakistan Institute of Development Economics
Islamabad
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Pakistan Institute of Development Economics
P.O. Box 1091, Islamabad, Pakistan

CERTIFICATE

This is to certify that this thesis entitled: **"Estimating Multidimensional Poverty Index and Its Growth Trajectories Using SEM: A case Study of Pakistan".** submitted by **Mr. Umair Khan** is accepted in its present form by the School of Economics, Pakistan Institute of Development Economics (PIDE), Islamabad as satisfying the requirements for partial fulfillment of the degree in Master of Philosophy in Econometrics.

Supervisor: Dr. Ahsan ul Haq Signature: _____

External Examiner: Dr. Zahid Asghar Signature: _____

Head,
PIDE School of Economics: Dr. Shujaat Farooq Signature: _____

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I Umair Khan hereby state that my MPhil thesis titled Estimating Multidimensional Poverty Index and Its Growth Trajectories using SEM: A case study of Pakistan is my own work and has not been submitted previously by me for taking any degree from Pakistan Institute of Development Economics or anywhere else in the country/world.

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Date 18/11/2022

Umair Khan

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"All praises to **Almighty ALLAH**, to whom belongs whatever is in the heavens and whatever is in the earth, and to Him belongs [all] praise in the Hereafter. And He is the Wise, the Acquainted". And who bestowed us the perfect code of life through His Prophet, **Hazrat Muhammad** (**P.B.U.H**).

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ABSTRACT

In this study, we estimate poverty in the form of a composite index by aggregates their respective indicators into a scalar score. In this study the basic idea is to capture the broader dimensions of poverty such as education, sanitation, housing, health, and other aspects as well. The analysis is based on Pakistan Social and Living Standard Measurement (PSLM) Survey 2014-15 and 2019-20 collected by the Pakistan Bureau of Statistics (PBS) is used to measure poverty at the national, regional and provincial level and providing empirical evidence on its growth trajectories as will to examine the poverty status of a particular region or province over time. In this study SEM approach is used for aggregating indicators into a composite MPI. Multiple-group comparisons in structural equation modelling were used for analysis of differences in the measurement model across provincial-wise as well as for urban and rural regions. The results of the study revealed substantial variations between urban and rural respondents in the conceptualisation of poverty. The results indicate that each sub-population consider respective items of population differently. Its means that the concept and meaning of poverty in different regions and provinces is different.

The results of the study showed that the poverty level in rural areas is higher than urban areas. By comparing the poverty level in provincial wise Panjab has lowest level of poverty, and Baluchistan has worst situation as compare to the rest of provinces. For the observation of change over time in MPI we use latent growth model. The results revealed that there is reduction of poverty observed over time, but the reduction level vary for the different regions and provinces.

Keywords: Multidimensional Poverty Index, Structural Equation Modelling, PSLM, Confirmatory Factor Analysis, Latent Growth Curve Model

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LIST OF ABBREVIATIONS

ANOVA	Analysis of variance
ATM	Automated teller Machine
BISP	Benazir Income Support Program
CFA	Confirmatory Factor Analysis
CFI	Confirmatory Fit Index
CHSD	Cameroon Household Survey Data
CMPI	Colombian Multidimensional Poverty Index
EDE	Equally Distributed Equivalent
EFA	Exploratory Factor Analysis
EOBI	Employees old age benefit
FY	Fiscal Year
GDP	Gross Domestic Product
HDI	Human Development Index
HIES	Household Integrated Economic Survey
HR	Human Resources
IFA	Individual Financial Assistance
IFAD	International Fund for Agricultural Development
IFL	Interest Free Loans
KMO MSA	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
KPK	Khyber Pakhtunkhwa
LGCMs	Latent Growth Curve Models
LPG	Liquefied Petroleum Gas
NPGP	National Poverty Graduation Programme
NSER	National Socio-Economic Registry
MM	Measurement Model
MPI	Multidimensional Poverty Index
OPHI	Oxford Poverty and Human Development Initiative
PBM	Pakistan Bait-ul-Mal
PBS	Pakistan Bureau of Statistics
PIDE	Pakistan Institute of Development Economics
PMT	Proxy Means Test
PRSP	Poverty Reduction Strategy Paper

PPAF	Pakistan Poverty Alleviation Fund
PPP	Purchasing Power Parity
PSLM	Pakistan Social and Living Standard Measurement Survey
PWDs	Persons with Disabilities
RCC	Reinforced Cement Concrete
RMSEA	Root Mean Squared Error of Approximation
SDG	Sustainable Development Goals
SEM	Structural Equation Modeling
TLI	Tucker-Lewis's index
UNDP	United Nations Development Program
WB	World Bank
WWF	Workers Welfare Fund

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

The term poverty is a broadly used word that covers a broad array of definitions. Researchers have slight deviations when defining and measuring poverty. This has led to various methods of poverty measurement. These measurements or indices recently have started incorporating a multidimensional approach. It is now broadly understood that poverty is multidimensional in character; the Human Development Index (HDI), for example, recognizes the role of health and education in addition to socio economic levels.

The classical methods of measuring poverty are one-dimensional, usually expenditure or per capita income. These methods based on poverty lines i.e. absolute or relative that divide the population between the poor and the non-poor. In absolute measures, the minimum threshold amount required for the minimum standard of living. In relative measures, the threshold is set as a certain percentage of the median or average income (Foster & Santos, 2013; Stoyanova & Tonkin, 2018). But poverty is a complex multidimensional phenomenon whose scope is not restricted to the income sufficiency approach but extends to the situation of health, malnutrition, education, and other basic environmental and living standers (Chan & Wong, 2020; Flores-Jiménez et al., 2010). Moreover, various poverty dimensions are correlated with each other (Bellani & D'Ambrosio, 2011; Jonathan Bradshaw & Finch, 2003; Costa, 2020).

Poverty is not a static phenomenon, but it changes with time. Therefore, it is also necessary to analyze its dynamic aspects for understanding its different fields. According to Wardanaa and Sarib (2020), the results drawn from the dynamic poverty analysis should be different as compared to the results drawn from the cross-sectional nature of poverty analysis due to the organization of the poor into two groups, i.e., chronic poverty, which lasts for a long period

and transient poverty which lasts for relatively a short period. Traditional and static poverty measurement becomes less applicable in recent times. According to Smith and Middleton (2007), it exhaustively understands poverty would not be achieved from its static Analysis. So, due to these shortcomings of poverty measurements in static form, it becomes essential that the dynamic nature of poverty analyze as we. The dynamic measurement of poverty is predictable to enhance policies' efficiency (Dacuycuy et al., 2019; Smith & Middleton, 2007).

Measurement of poverty is a complicated system; it is not just obtained by a multiplicity of different factors (Dongping, 2007; Zhichang, 2007). Poverty is the incapacity of attaining a minimum living standard, but this concept arises several questions: what is the minimum living standard? how will measure the level of welfare? and how will we measure poverty? therefore, it is important to consider poverty as a theoretical concept for the measurement of poverty index and find a measurement of indirect form based on direct measurements of indicators that can compute directly (Flores-Jiménez et al., 2010). According to Israr et al. (2020), the measurement of multidimensional poverty generally comprises an index's structure, including information of indicators for selected dimensions.

Poverty has been existing and continuing for a long time in many countries of the world. Therefore, poverty alleviation remained an important subject of policy in many countries. To understand the threats and problems arising from poverty, it is necessary to find its dimensions, dynamic aspects, and its measurement methods (Chakravarty, 2019).

From the last decades, an incredible increase in the literature in methodology and applications for MPI measurement. There are different measurement methods used in different research studies for the measurement of MPI. A large number of studies used the Alkire and Foster model for the measurement of MPI, to mention but a few we highlight are Mahmood and Hussain (2020), Najam (2020), Workneh and Eshete (2020), Suppa (2018), Sabina Alkire and Shen (2017). In the same way, large number of researchers used fuzzy techniques for the

measurement of MPI in their studies, which include; (2019), Belhadj (2012), Annoni et al. (2008). In some studies, the Structural Equation Modeling (SEM) method was also used for the measurement of multidimensional poverty like; Pasha (2017), Ningaye et al. (2013), Ningaye (2011), Flores-Jiménez et al. (2010). While some other studies used some other techniques and methods for the measurement of MPI like; Catalán (2019) used Monte Carlo study based on factor mixture models, Padda and Hameed (2018) used the principal factor analysis technique, and Antony and Rao (2007) used Analysis of variance (ANOVA), discriminant function analysis, and factor analysis in their study. The poverty measurement's basic objective is to find such a sound theoretically and methodologically to be used in policy recommendations (J Bradshaw, 2000).

Differences between the various approaches are however much smaller as far as the determinants of multidimensional poverty are concerned. This analysis may change with a new focus on using these techniques for a pre and post implementation assessment tool. To be able to effectively assess impacts of aid within a community, a large variety of factors need to be analysed; direct and indirect effects need to be taken into account; and the assessment needs to be flexible with both time and error in measurement.

1.2 Objectives of the Study

The basic objective of this study is to operationalize poverty in the form of a composite index that aggregates a range of individual indicators into a scalar score. The core idea hereby is to move beyond material aspects and capture the broader dimensions of wellbeing such as health, education, or social capital. There are numerous approaches to measuring multidimensional poverty. However, SEM offers a robust platform for a deeper understanding of poverty. Furthermore, an overview of SEM and several other approaches for the measurement of poverty are also necessary to be addressed. Secondly, this study will also be providing

empirical evidence on MPI growth trajectories as will to examine the poverty status of a particular region or province in different times using Latent Growth Model (LGM).

1.3 Significance of the Study

To be able to effectively assess the complex nature of MPI, a large variety of factors need to be analysed; direct and indirect effects need to be taken into account; and the assessment needs to be flexible with both time and error in measurement. SEM allows for the incorporation and understanding of multiple relationships within this complicated nature of MPI. Compare to existing approach of Alkire-Foster which based on, expert opinion weights, frequency-based weights and equal weights to poverty indicators. While, in SEM approach weights are assigned on the base of correlation structures among poverty indicators.

Secondly, the use of latent variables (use in this study) is a concept within the area of SEM that allows the researcher to represent variables that can prove difficult to analyse through basic observations. Instead of using the idea of an index of indicators, SEM is able to avoid the errors accumulated from the summation of variables, whether weighted or not. The analysis of variance and covariance between multiple observable indicator variables allows for representation of these latent variables.

1.4 Organization of the Study

The rest of the study is organized as follow: Chapter 2 shed light on the existing literature of different approaches for the measurement of MPI. Followed by chapter 3 which contain a comprehensive overview of related policies and programs for poverty alleviation in Pakistan. Chapter 4 highlights different methods/techniques of poverty measurement, in chapter 5 results and analysis are discussed and chapter 6 is about conclusion, recommendations and limitations.

CHAPTER 2

LITERATURE REVIEW

2.1 Definitional Debate on Poverty

To measure poverty, one first needs to know that what is poverty? different people naturally have different opinions of what 'poverty' means. This is true between countries well as within a given country. Richer countries tend to have higher lines when converted to a common currency at exchange rates that attempt to assure Purchasing Power Parity (PPP). Among poor countries, there is very little income gradient in the poverty lines-absolute consumption needs tend to dominate in a poor country. But, as incomes rise, societies naturally tend to rise their views of what minimum standard of living is deemed acceptable. So, poverty lines rise with mean consumption (Ravallion, 2003) .

Poverty is a complex phenomenon which can be defined in multiple ways, each capturing a different dimension of the subject. The classical or one-dimensional poverty approach, i.e., income-based or consumption-based, shows a biased and imperfect knowledge to address poverty. Ashaal and Bakri (2019) revealed that income-indicators could only measure a certain degree of poverty. Therefore, recent studies trends are shifting from the traditional approach to multidimensional poverty analyses. Different weights are given in multidimensional poverty measurement to justify the unequal significance of different poverty dimensions and improve the classification between poor and non-poor (Catalán, 2019).

Multidimensional poverty focuses on multiple dimensions of people's living standards, such as their income, life expectancy, and educational standards. More accurately, a specific and standard level is set for each attribute. Shortcomings of different attributes from a specific standard for different people are accumulated into a total indicator of poverty (Chakravarty, 2019). Similarly, the study of Pomati and Nandy (2020) focused on different poverty

dimensions using the Consensual Approach to poverty measurement that explained how can update different poverty measurement frameworks. The study of Pasha (2017) examined the outcomes of various weighting structures within the MPI. In his study, he tried to resolve the different definitions of poverty due to varying indicators.

With time, poverty's static nature becomes less important; now, poverty's dynamic nature becomes most relevant for researchers and policymakers. Various researchers analyzed the dynamic nature of poverty in their studies, including the study of Wardanaa and Sarib (2020); Rahayu et al. (2020); Costa and De Angelis (2015); Wardanaa and Sarib (2020), which examined the dynamic nature of poverty. So, poverty is a complex phenomenon both in its static as well as in its dynamic nature.

2.2 Literature on measurement of MPI

In a pioneering contribution, (Sen, 1976) regarded the poverty measurement problem as involving two exercises: the identification of the poor; and (ii) the aggregation of the characteristics of the poor into an overall indicator that quantifies the extent of poverty. In the literature, the first problem is mostly solved by the income method, which requires the specification of a poverty line representing the income required for a subsistence standard of living. A person is said to be poor if his income falls below the poverty line. On the aggregation issue, He criticized two crude indicators of poverty, the headcount ratio (the proportion of persons with incomes below the poverty line) and the income gap ratio (the difference between the poverty line and the average income of the poor, expressed as a proportion of the poverty line), because they remain unaltered under a transfer of income between two poor persons and the former also does not change if a poor person becomes poorer due to a reduction in his income. He also characterized axiomatically a more sophisticated index of poverty.

Many studies have used different techniques and dimensions for the MPI measurement, which include; Catalán (2019) used a Monte Carlo study based on factor mixture models and calculated a series of unit and multidimensional poverty measures with different reliabilities for pre-defined groups. Their results showed that reliability checks should be an efficient practice in poverty measurement. Their study provided guidelines for the interpretation of the properties of unreliability upon suitable population classification.

The paper of Tigre (2018) used the Alkire and Foster method for the multidimensional poverty. The study results revealed high multidimensional poverty in Ethiopia in general and its rural areas in particular. The indicator of living standards put up the high share (more than 85%) to multidimensional poverty while education contributed about 14% and health contributed the least (less than 1%).

The study of Mohanty et al. (2018) Used data from 4290 households and the Alkire–Foster method, and their study estimated multidimensional Poverty for Shan and Chin states in Myanmar. They used five dimensions and twelve indicators for the multidimensional poverty index.

Multidimensional poverty is not an issue for developing nations. It also faces by some advanced nations too as the study of Suppa (2018) presented an inclusive multidimensional poverty index for a developed country like Germany. He applied Alkire and Foster model. In his study, he included material deficiency and employment as important indicators. The study proved that poverty varies over time between subpopulations. The study results suggested that the multidimensional approach enhanced distinctive insights, which were neither offered by a single indicator nor by a dashboard approach. The study results also revealed a disagreement between multidimensional and income poverty measures to decide who is poor. Sabina Alkire and Shen (2017) presented the global MPI for China. The study results revealed that education, safe drinking water, nutrition, and cooking fuel almost complete overall non-monetary poverty

in China. They used the same analysis for subgroups, including geographic areas (urban /rural, west/central/east, provinces), and social features such as age, education level, gender of the household head, household size, and marital status. The results proved that level of poverty varies meaningfully across different subgroups.

The study of Saleem et al. (2021)investigated the multidimensional poverty in urban and rural areas of Pakistan. They used main three dimensions of poverty including education, health and living standard. They used PSLM data of household. The results of the study revealed during all periods of time poverty level is high in rural regions as compare to urban regions. They suggested that it is a fundamental obligation of the govt to provide basic and sustainable development necessities like health, food and education and for the wellbeing of their people.

Angulo et al. (2016) presented the Colombian Multidimensional Poverty Index (CMPI). They used Alkire and Foster methodology for the measurement of CMPI. Their CMPI was composed of five dimensions (childhood and youth conditions, household members' education, employment, health, access to household utilities, and living conditions). A nested weighting structure was used in the study, in which each dimension weighted equally, like every indicator in a specific dimension. The study results showed that poverty decreased in Colombia between 1997 and 2010, but imbalances between poor and rich did not reduce. The study of Flores-Jiménez et al. (2010) examined the determinants of the poverty index in Mexico. They developed a complete structural regression model, a composite of two sub-models: one was the measurement model, and the other was the structure model, which used observed and latent variables; both models included dependent as well as independent variables for the determination of the integrated measure of poverty.

The study of Steinert et al. (2018) examined the validity of composite indices of the poverty for KwaZulu-Natal, South Africa using cross section data of 2477 households selected from the urban and rural areas. He used multiple group comparison in SEM for testing the validity

and reliability for the observing of differences between rural and urban regions. The results of the study revealed that there was exist a significant difference between rural and urban households both in terms of concept and meaning of poverty as well importance for various poverty indicators. They concluded that the validity of a unique measurement model cannot be confirmed across difference regions and for different populations. Their study concluded that for the measurement of poverty a researcher should be sensitive to identify the correct indicators of a particular region.

Multidimensional poverty is not restricted to underdeveloped and developing nations. But still, it is in its severe shape in underdeveloped nations as the study of Trani et al. (2016) revealed that nearly all Afghan adults are deprived in at least one dimension and specially those residing in rural areas. Their study aimed to understand poverty in Afghanistan. The study calculated one index using two weights structures, the adjusted headcount ratio, and part of the multidimensional poverty measures.

Vijaya et al. (2014) measured multidimensional poverty for India by using the classical approach (income approach) of using household instead of the individual as the analysis unit. Measures on household-level set impartial in case of gender to ignore intra-household differences in resource allocation. The results showed that an individual-level measure could classify considerable gender differences in poverty.

Multidimensional poverty's dimensions show different natures in different nations and even in different regions of the same nations. The study of Ningaye et al. (2013) examined that different regions were affected by a different type of poverty, and there is no unique type of poverty in a single region. Their study proved that dimensional scores are more suitable in identifying poverty as compared to previous approaches. They used the SEM approach for five dimensions of welfare indicators measurement.

The study of Mitra et al. (2013) deals with selecting dimensions and setting weights for multidimensional poverty measurement using quantitative and qualitative methods. They estimate the multidimensional poverty measures developed by Alkire and Foster. Two discussion groups are organized to select related dimensions and their appropriate ordering: one group has lived experience, and the other group consists of people with mental health or research expertise. For the conversion of dimensions rankings to weights, different methods were used in the study. The ordering and selection of dimensions vary between the discussion groups, as did the resulting poverty measures.

Belhadj (2012) used the fuzzy theory approach to offer a new weighting structure for the dimensions. These weights play a vital role in setting the trade-off between the dimensions.

PASANEN (2012) examined the relationship between poverty indicators, monetary expenditure, and MPI. MPI composite of three indicators, health, education, and living standards. The study carried on household level and used two-staged structural equation modeling (confirmatory factor analysis and path analysis) techniques. The study results showed that expenditure and multidimensional poverty have a significant association with households, and this association is stronger on the village level. Infrastructure has a significant impact on poverty at the village level. The study also suggested that poverty can be minimized by improving communal services.

Similarly, the study of Rahayu et al. (2020) examined the elements of poverty in rural and urban villages. They used the dynamic panel data regression method in their study. Their study revealed that rural villages have a greater number of poor people than urban villages.

The study of Djahini-Afawoubo and Couchoro (2020) examined the dynamic nature of multidimensional poverty using a counting approach in Togo. They used six dimensions of poverty (education, employment, services, public health, housing and sanitation, and assets).

They found a significant decrease of about 21 percentage in multidimensional poverty between 2006 and 2015 in Togo. Similarly The study of Sabina Alkire and Fang (2019) used Panel data set for constructing MPI for China. The results of their study found multidimensional poverty was higher in rural areas and backward provinces.

The study of Costa and De Angelis (2015) analyzed the longitudinal phenomenon of poverty. they interpreted poverty as a latent variable. In their study they used mixture latent Markov model for the achievement of two goals i.e., statistics as well as dynamic analysis of poverty. They used different socio-economic indicators as covariates for the measurement of poverty in a multivariate framework and identifying which are the significant and main factors of statistic and dynamic poverty. The study identified two groups of households which has different dynamic characteristics. Furthermore, the socio-economic indicators such as employment, education and residential position showed a direct relationship to static poverty.

The study of Hojman and Kast (2009) measured poverty changes with time. They illustrated the fractional status over income dynamics. They Compared two decades of income dynamics in the United States; income dynamics of the 1980s and income dynamics of the 1990s. They also compared the income dynamics of three advanced nations and concluded Germany and United States were dominated the United Kingdom. Similarly the study of Hajdu (2009) measured poverty in multivariate framework by applying SEM approach. They focused on the estimating path coefficient on one side and testing their significant on the other side by taking household as unit of measurement.

the study of Wardanaa and Sarib (2020), which examined the dynamic nature of poverty in Indonesia from 2008 to 2010. The quantitative method with the component approach of the Equally Distributed Equivalent (EDE) poverty gap was used as a study method to show the transient component of poverty and the chronic poverty component. For the determinant inquiry of the transient component of poverty and a chronic poverty component, the regression

method used was the tobit method. The results of the study revealed that chronic poverty was dominated in Indonesia.

Sabina Alkire and Santos (2010) presented MPI for 104 developing countries. They estimated multidimensional poverty using micro datasets (household surveys) for many countries for the first time. They used Alkire and Foster poverty multidimensional measures, which consisted of ten indicators matching to HDI indicators, i.e., education, health, and standard of living. The results of the study revealed that Sub-Saharan Africa has the highest poverty incidence.

2.3 Literature on Application of SEM to Calculate MPI

Various studies had been conducted by different researchers using SEM for the estimation of MPI including; Ningaye et al. (2013) used SEM for the measurement of MPI for Cameroon. They used data from Cameroon Household Survey Data (CHSD III) carried out by the NISC in December 2007.The result of their study showed that Different regions are suffered by a particular type of poverty while no form of poverty is unique to a single region. Their study proved that dimensional scores are more suitable in identifying poverty as compare to previous approaches.

The paper Kusuma et al. (2021) used SEM with Partial Least Square (PLS) to analyze different factors of poverty in Papua Province. They use four latent variables (economy, poverty, Health and Human Resources (HR), taking sixteen indicators. The result of the study showed that economy and health have significant impact on poverty.

Chan and Wong (2020) used Structural equation modelling for the relationship of different dimensions i,e. material, monetary and social dimensions of MPI in Hong Kong. The results of the study proved that the impact of income on poverty was partly mediated by the social and material dimensions of subjective poverty. For the age wise comparison elder people were

more influenced by deprivation. While younger people are more influenced by social exclusion.

Ningaye (2011) studied Ethno-cultural diversity and multidimensional poverty differential in Cameroon by Applying SEM approach. His study revealed that different dimensions of poverty significantly different from each other.

Flores-Jiménez et al. (2010) developed a complete structural regression model, composite of two sub models: one was the measurement model and other was the structure model which used observed and latent variables, both models included dependent as well as independent variables for the determination of the integrated measure of poverty.

Hajdu (2009) applied SEM technique for the measurement of poverty in a multivariate approach. He focused on estimating structural path coefficients on one side and on the other side focused on testing their significance.

2.4 Measurement of MPI in Pakistan

In Pakistan's case, different studies also exist that measured the MPI for Pakistan, which includes. estimated MPI for Pakistan using the five dimensions of poverty, i.e., education, health facility, basic needs, quality of housing, and living standards, with eleven indicators. Their study used micro-level data from Pakistan Social and Living Standard Measurement Survey (PSLM) Round VII (2013-14) and used the Alkire-Foster model for Analysis.

estimated multidimensional poverty in Pakistan by using the Alkire-Foster methodology. Their Analysis was based on PSLM Survey 2004-05 and 2014-15. Their study adopted expert opinion weights, frequency-based weights, and equal weights for the measurement of MPI at national and provincial levels. The study results showed the MPI estimates ranged from 14% to 20% at the national level and were very sensitive in the choice of weights. However, the results for equal weights underestimate the magnitude of poverty. Moreover, the time-specific

inquiry of poverty disclosed that poverty's intensity has negligible influence on reducing Multidimensional Poverty in Pakistan.

A study by Khan et al. (2016) estimated the degree of multidimensional poverty region-wise in urban areas of Pakistan along with percent share of each sub-group in poverty index and taking data of household integrated economic survey (HIES/PSLM) five data sets (from 1998 to 2008). The total impact of urban poverty at the national level in Pakistan was estimated around 29, 32, 25, 29, and 28 %, respectively, in the given periods. The occurrence of multidimensional poverty on average marginally reduced across the regions over about ten years spam.

Padda and Hameed (2018) estimated multidimensional poverty for rural Pakistan by applying principal component analysis. The study found that 44% of rural Pakistan households are poor, lasting a deficiency of clean drinking water, insufficient sanitation services, not proper energy facilities, and poor housing conditions. In this study, they analysed poverty on district level and suggested that policymakers take actions at the district level to reduce poverty.

Similarly, for analyzing the dynamic nature of Poverty in Pakistan, a few studies were conducted by different researchers in which include; The study of Salahuddin and Zaman (2012), which used Alkire and Foster methods for the measurement of MPI for Pakistan from 1998 to 2006 using the data from PSLM and HIES. Their study showed that Health and Education are the critical dimensions of multidimensional poverty, and these two dimensions showed a dramatic increase in poverty.

The study Arif and Farooq (2014) analyzed the dynamic nature of poverty in Pakistan's rural areas. They used a panel household survey of three waves conducted in 2001, 2004, and 2010—the estimated poverty using the official poverty line. Based on the component and the spell approaches, transitory and chronic poverty were estimated discretely for the two and three

waves. The study results revealed that, based on spell approach on the two waves, about 9 percent of the households were poor in those periods. However, it falls to 4 percent when three waves take into consideration. While using the spelling approach, about 16 to 18 percent of the household were chronically poor.

2.5 Concluding Remarks

Different researchers used different techniques and approaches for the measurement of MPI. Voth-Gaeddert and Oerther (2014) gave an overview of SEM and various other methods for intervention assessment tools of MPI. He found that SEM propose a robust technique for the establishment of such a tool. Therefore, in this study, the structural equation modeling technique will be used to estimate MPI and its growth trajectories in Pakistan

CHAPTER 3

OVEREVIEW OF RELEVANT POLICIES/PROGRAMES FOR POVERTY ALLEVIATION IN PAKISTAN

This chapter contains three sections, first section about historical background of govt reforms for poverty alleviation, second section is an overview of pro-poverty expenditures and third section contains an overview of social safety net programs.

3.1 Governmental reforms for the alleviation of poverty

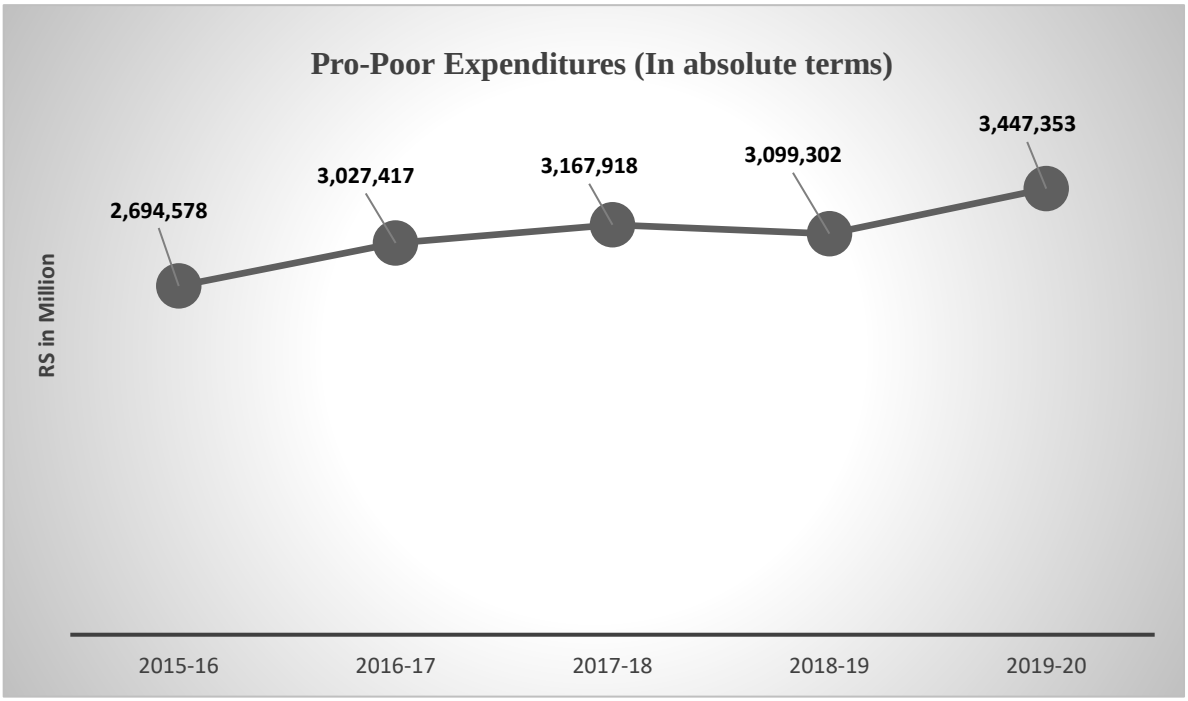
Pakistan is not in a position to adopt a general or universal social protection program which cover all its population. However, a number of initiatives are taken by the govt for the improvement of the poor to assis them economically by creating employment and income opportunities. For this purpose, govt has been implemented several reforms. Decentralization plan launched in March 2000, is an important governance reform. It replaced the highly centralized government with a three-tier local government system that institutes "people-centered, rights and responsibility-based, and service oriented" government structures. Under decentralization, health and education, which are important poverty determinants have been transferred to lower local governments and district level. According to this reform now the provinces and local government mainly responsible for the provision of services and will be countable for any failure in term of political loss. A number of civil service reforms have been implemented by the government to improve public sector and make it more accountable and approachable to the citizens. For this purpose, the launch micro-finance and the establishment of Khushali bank in 2000 to support poor through income generating strategy.

Pakistan Bait-ul-Mal (PBM) was established in 1992. Its basic objective was poverty alleviation and specially focus on orphans, widows, disabled, poor and needy people irrespective of caste, sex, religion or creed. It provides residential accommodation, educational

assistance and necessary facilities promote self-employment schemes and free medical treatment. Federal government is the main financing source of PBM but it also receives small grants from the Zakat funds as well as from provincial and local governments. Moreover, zakat and ushr department was set up in 1980, which work based on Islamic thoughts in which rich people should pay a specific amount at the rate of 2.5% on their wealth to the poor.

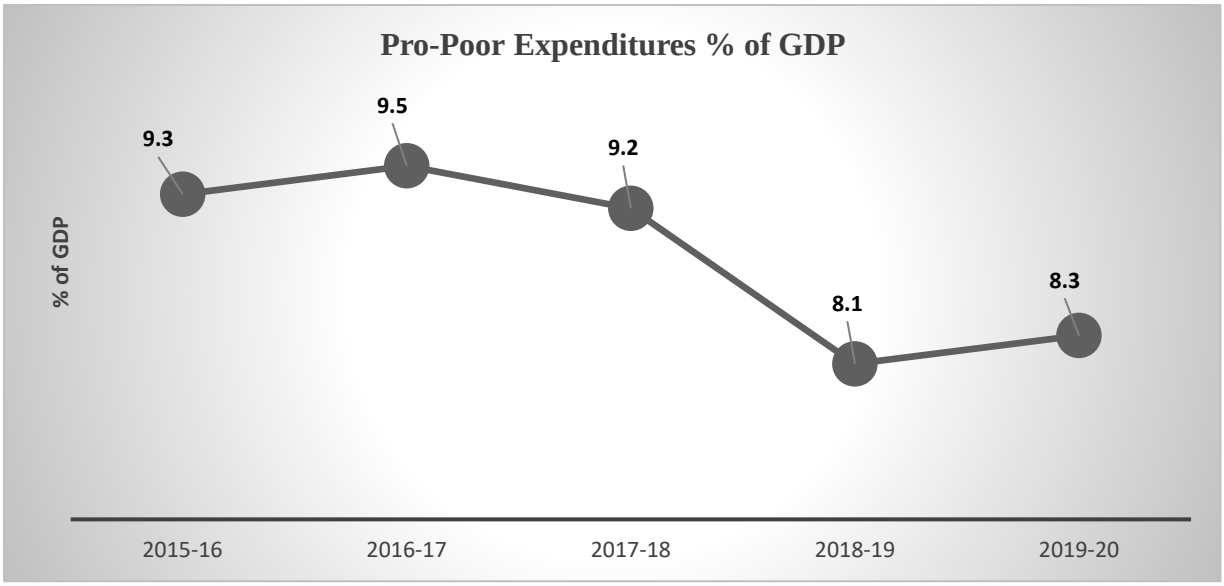
3.2 Pro-Poor Expenditures of the Govt of Pakistan

Pro-poor expenditure in absolute terms slightly increased from Rs. 2,694,578 million to Rs 3,447,353 million from 2015-16 to 2019-20. as shown in below chart.



Source: External Finance Policy Wing, Finance Division

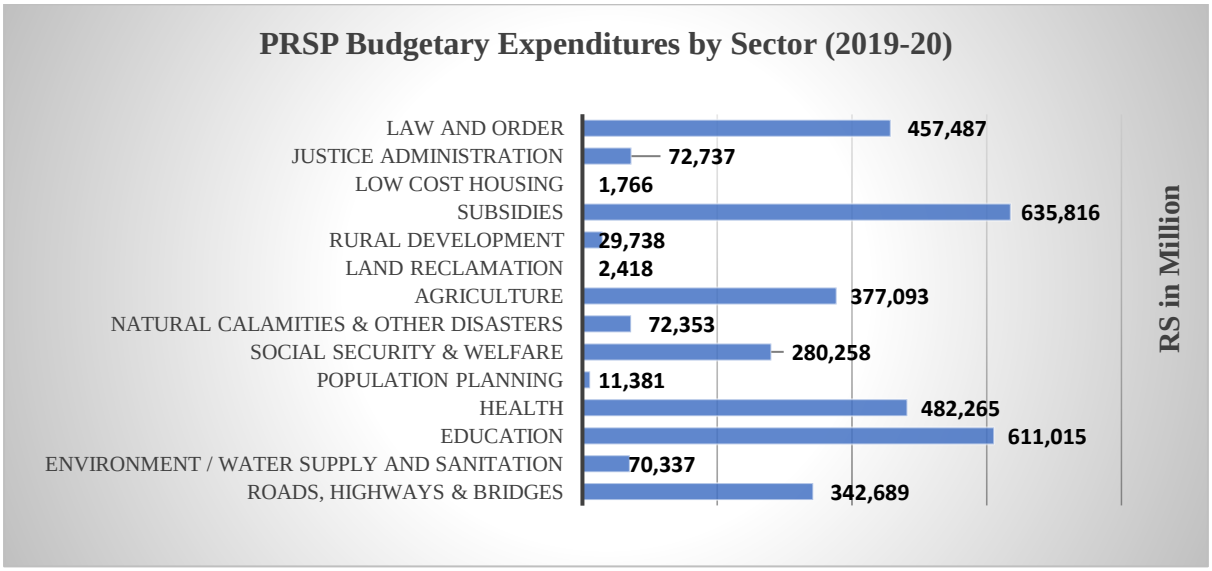
However, by taking it in percentage terms of Gross Domestic Product (GDP) it is decreased as shown in below chart.



Source: External Finance Policy Wing, Finance Division

3.2.1 Poverty Reduction Strategy Paper (PRSP) Budgetary Expenditures by Sector

Sect-wise budgetary expenditure indicates that a huge portion is allocated for subsidies followed by education, health and law and order expenditures. There is negligible allocation for population planning, low-cost housing and land reclamation as shown in the chart.



Source: External Finance Policy Wing, Finance Division

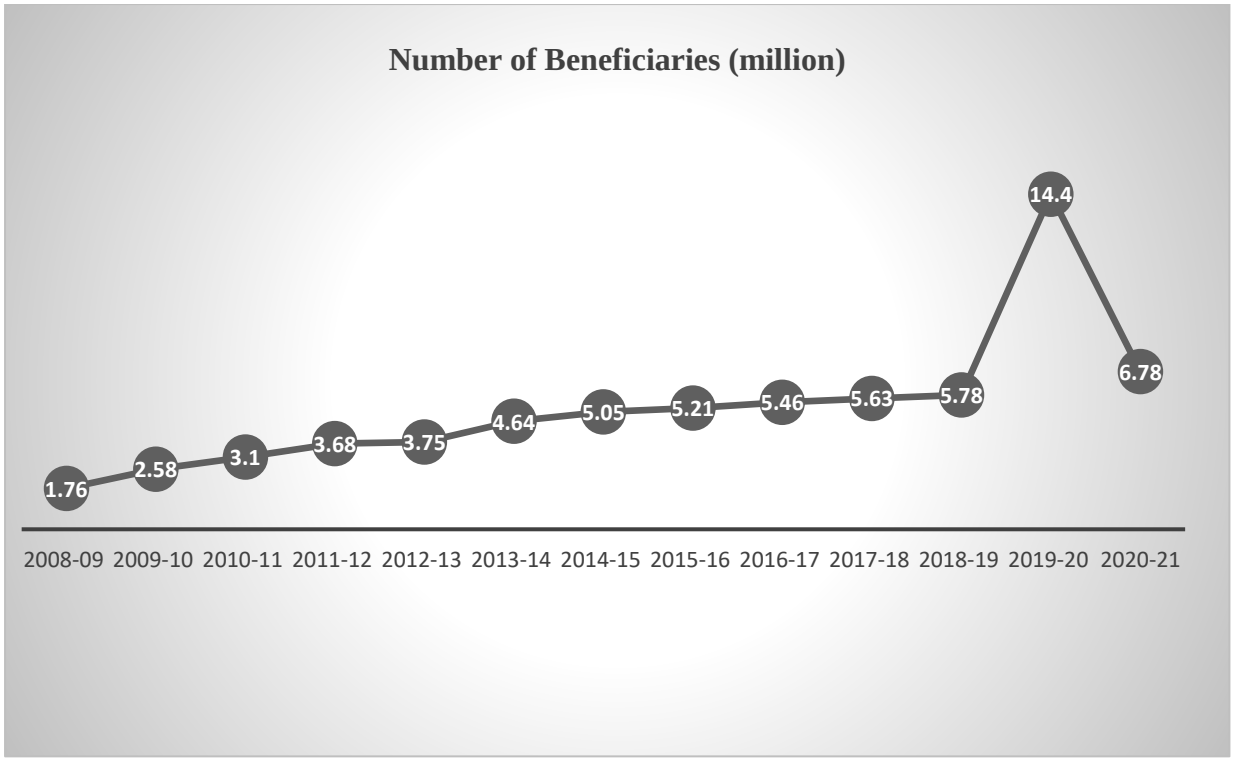
3.3 Social Safety Net Programs in Pakistan

Social safety net programs lie under umbrella of social security & welfare and investment. Key social safety initiatives included programs e.g., Benazir Income Support Program (BISP), Pakistan Poverty Alleviation Fund (PPAF), Pakistan Baitul Mal (PBM), Workers Welfare Fund (WWF), Employees old age benefit (EOBI) etc. After the launch of "Ehsaas Program" all these social safety programs are now under the umbrella of Ehsaas Program.

3.3.1 Benazir Income Support Program (BISP)

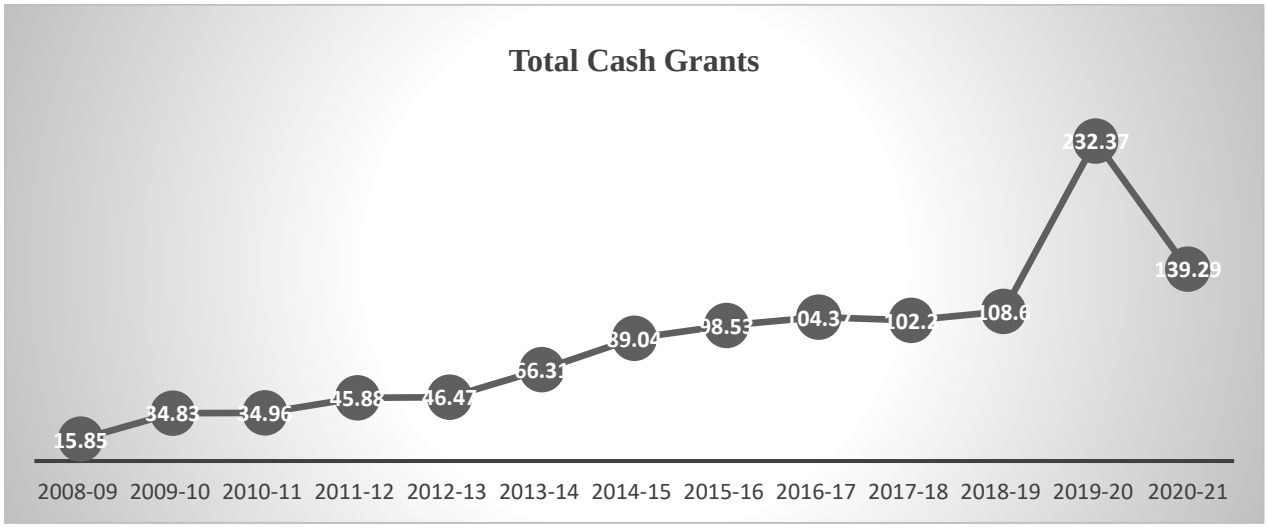
BISP promulgated by the government of Pakistan in July 2008. The main feature of the program is that, the data is based on people's socioeconomic status that includes indicators like types of housing, house size, child's education status, toilet facilities, number and worth of assets, stock ownerships, land holdings, etc. The data is then stored in the National Socio-Economic Registry (NSER) and the welfare status of the households is derived trough Proxy Means Test (PMT) and the scores are recorded between 1-100 – where 1 is classified as the most extreme case of poverty in the pool. According to the government reports the data covers nearly 85% of the total population eligible to receive the cash transfer. The eligible applicants can then retrieve their amount through an Automated teller Machine (ATM) or services like Easy-paisa and bank withdrawal can also be used.

In its first year nearly 1.76 million families benefited from this program, however this number has increased to about 14.4 million in by 2019-20.



Source: Benazir Income Support Programme (BISP)

The total amount received from the govt of Pakistan also increase from 2008 to 20120 as shown in chart below:



Source: Benazir Income Support Programme (BISP)

This program has significantly contributed to Sustainable Development Goals (SDG) of education, gender inequality and no poverty. However, with the passage of time there have been a number of issues raised. Misallocations of fund and leakages are the two major problems

confronted by the policy implementers. The report of govt of Pakistan in December 2019, exposed that nearly 0.8 million ineligible people were benefiting from the program – among which nearly 2000 were government employees of executive positions (Grade 17-21) (DAWN, 2020). Correspondingly, a scores of applicants have reported that the sum they receive is often less than the amount allocated, which does less in affecting their overall monthly expenditure (Cheema, et al., 2020).

Another problem with the policy is the high inflation due to which real impact of transfer through this program is decrease. Moreover, according to the program is generating very small improvements to beneficiaries' consumption expenditures. Thus, BISP is not currently having a statistically significant effect on reducing chronic poverty (Cheema, et al., 2020). However, on the other side according to an evaluation report by Pakistan Institute of Development Economics (PIDE), the BISP has significantly protected the poorest segments from the inflationary shocks (Farooq, 2014). Similarly, a report by the World Bank (WB) indicates that there has been a positive impact on women empowerment of this programme (Ambler & De Brauw, 2017).

3.3.2 Pakistan Poverty Alleviation Fund (PPAF)

PPAF was established in 1997. The basic objective of this program is to support poor through loans. Policy guidelines for PPAF are designed by the board of directors, which contains nine members from the civil society and three members from the government. PPAF works as a supplier that distributes its credit through fellow organizations mainly non-profit organizations.

Different programs work under PPAF which are.

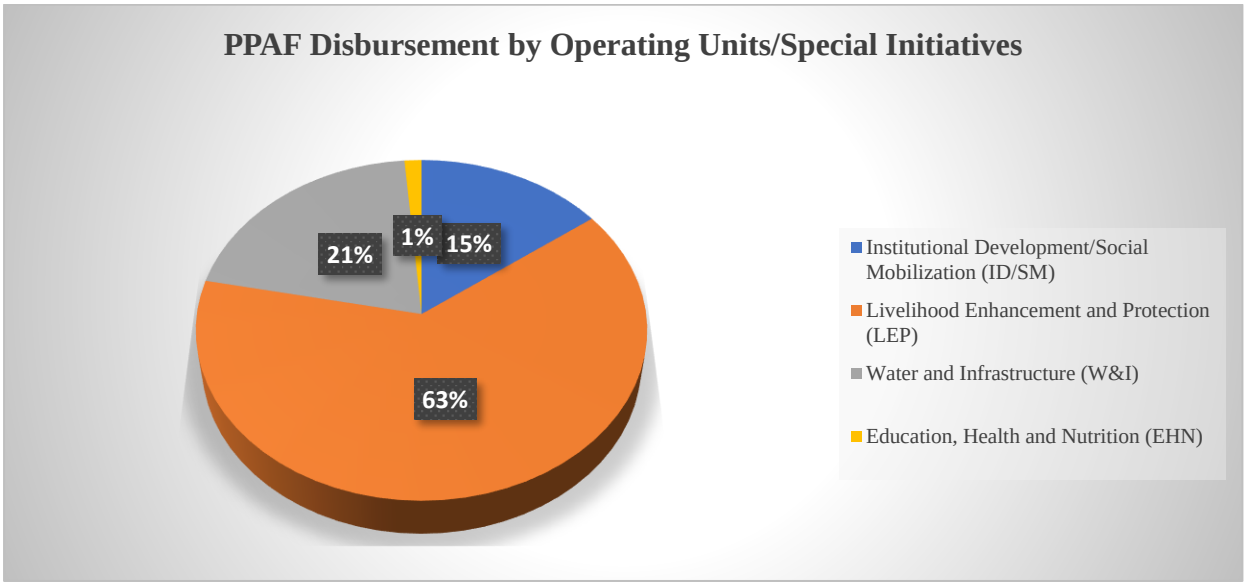
- National Poverty Graduation Programme (NPGP)
- Interest Free Loans (IFL)
- Growth for Rural Advancement and Sustainable Progress

- Livelihood Support and Promotion of Small Community Infrastructure
- Building Resilience to Disasters & Climate Change
- Programme for Poverty Reduction
- Development of Hydropower and Renewable Project
- Poverty Graduation Programme for Afghan Refugees
- Developing Sustainable Livelihoods in Dairy Value Chain
- Tabeer-o-Tameer Fund
- Balochistan Education Initiative
- Continued support to PPAF's Established Schools in Sindh
- Rehabilitation of Physically Challenged Persons Programme
- The Art Residency Programme

present government has launched the National Poverty Graduation Initiative (NPGI) under the poverty alleviation Program. The basic objective of this program is to empower the rural poor people and specially the youth and women to attain a higher standard of wellbeing. This is an initiative of PPAF, this program contributing to Ihsas amdan program supported by government of Pakistan and International Fund for Agricultural Development (IFAD). This is a six-year program from 2017-2023 and is funded by Govt of Pakistan and IFAD. The budget of this program is $150 million. The implementation of this program in 23 districts and 388 union councils of Pakistan. The program is designed in such a way that to pull out the poor people from the poverty circle through financial inclusion, social mobilization and livelihood development.

From the establishment of PPAF in 2000 till 2020 approximately Rs 224.64 billion has spent in about 144 districts. Under ehsaas PPAF 38,300 education, health, water, and infrastructure projects have completed, 30800 persons with disabilities rehabilitated and 124700 productive

assets have transferred to vulnerable households, In FY 2021 PPAF managed to disburse Rs 2,640.09 million to its partner organizations as shown in the below chart.



Source: Pakistan Poverty Alleviation Fund, Islamabad

3.3.3 Pakistan Baitul Mal

Under the flagship of "Ehsaas Program" PBM also contributing towards unmet needs by aiding destitute orphans, widows, Persons with Disabilities (PWDs) and other marginalized persons. PBM has disbursed an amount of Rs 2.705 billion in FY 2020 through its core projects and schemes. In FY 2021 Rs 6.105 billion has been allocated to PBM for implementation of schemes; i.e. women empowerment centres, School for rehabilitation of child labor, Dar-ul Ehsaas (orphanage), , Child Support Programme, Individual financial assistance and Ehsaas Kada (for shelter less senior citizen)etc.

following projects and schemes are functional are functional under Pakistan Baitul Mal:

- Individual Financial Assistance (IFA)
  - Medical
  - Education
  - General
- Panahgah

- Koi Bhooka Na Soye
- Women Empowerment Centres
- Dar-ul-Ehsaas
- Persons with Disabilities (PWDs)
- Pakistan Baitul Mal Schools for Rehabilitation of Child Labourers
- Persons with Disabilities (PWDs)
- Institutional Rehabilitation

3.3.4 Employees old age benefit (EOBI)

The EOBI is playing a key role in poverty reduction by paying grants and pension to retired employees and their families through various program such as old age pension, invalidity pension, survivors' pension, and old age gran. Currently EOBI has registered 225465 survivors' pensioners, 437472 Old-age pensioners and 11056 invalidity pensioners.

Main Features of the EOBI Schemes are

- **Old-age pension: receiving** on the age of 60 years of male employee and 55 years in case mine workers and female.
- **Invalidity pension** on sustaining invalidity affecting more than one third of normal of the insured person's earning.
- **Old-Age Grant: this is** for those employees which not satisfying the benchmark for old-age pension. The grant is paid in lump sum to insured persons who have less than fifteen years' insurable employment but attain the age of 60/55 years

The EOBI payments are a sustainable source of income for the insured employees and for their families who are live below the poverty.

3.3.5 Workers Welfare Fund (WWF)

Workers Welfare Fund (WWF) Ordinance in 1971 established Workers Welfare Fund to facilitate the industrial employees. The basic bjectives of this program the provision of basic

facilities like health, education and the development of residential colonies and flats for the workers and their families. This program also provides death grant and marriage compensation to the widow and daughter of the workers. FY2021 expenditures amounting to Rs 2.47 billion have been incurred on 33,679 scholarship cases, while Rs 573.44 million has been disbursed as marriage grants Rs 100,000 per worker benefitting 5736 workers' families. The WWF has also disbursed Rs 496.55 million as death grant Rs 500,000 per worker covering 994 cases of mishaps all over the country.

3.4 Way forward

From the last two decades the govt of Pakistan has remarkable phase in terms of performance and expansion of social safety net programs. Many innovative programmes have been conceptualized, rolled out and taken to scale and few existing programmes which were continued have undergone extensive and deep-rooted reform. But there is always a room for the improvement. The govt can improve the existing programs or launch new programs through govt-private partnership or through Non-Government Organizations (NGOs) and specially through Welfare-oriented NGOs, Edhi Welfare Trust is the best example for this type of category that operates a countrywide network of relief services such as ambulance, old houses, orphanage houses, women shelter houses, poor feeding houses, so the govt work with such welfare trust not only reduce the poverty level but the efficiency of the programs may also be increase.

CHAPTER 4

DATA AND METHODOLOGY

4.1 Data and Sample

The analysis is based on Pakistan Social and Living Standard Measurement Survey (PSLM) 2014-15 and 2019-20 collected by the Pakistan Bureau of Statistics (PBS) is used to measure poverty at the national, regional and provincial level and to observe changes over time. PSLM district level survey collected information on key social indicators which is the main source of estimation of multi-dimensional poverty. The data generated through surveys was used to assist the government in formulating the poverty reduction strategy, whereas provincial level surveys (Social & HIES) collected information on income and consumption. HIES data is used by planning commission for estimation of consumption-based poverty.

Moreover, PSLM questionnaire was not changed during the life of project, therefore, the situation of poverty can be better analysed through-out the time.

The data of 78635 and 160654 households in 2014-15 and 2019-20 respectively is taken from PSLM collected by PBS. The data set consist on a high percentage of Panjab and Sindh as compare to Khyber Pakhtunkhwa (KPK) and Baluchistan. Likewise, dataset consist on a high percentage of rural households as compare to urban. The dataset of 2014-14 round covers 78635 household whereas the sample share comprises of 64.93% of rural population and 35.07% of urban population. The percentage is almost same for the rural vs urban households in 2019-20 where the rural share is 68.9% and urban 31.1% of urban population. As we look to the provincial-wise, almost half of sample size consist on the household of belong to Panjab.

Table 4.1 Sample Size

Source: PSLM survey data 2014-15 and 2019-20

	2014-15		2019-20	
Provinces/regions	**Sample Size**	**Percentage**	**Sample Size**	**Percentage**
KPK	13082	16.6%	28633	17.8%
Panjab	36571	46.5%	79674	49.6%
Sindh	18735	23.8%	37106	23.1%
Baluchistan	10247	13.0%	15241	9.5%
Total	**78635**	**100.0**	**160654**	**100.0**
Rural	51058	64.93%	110672	68.9%
Urban	27677	35.07%	49982	31.1%

4.2 Different approaches used to estimate MPI

A number of approaches use to measure MPI, which includes dashboards, venn diagrams, the, statistical approaches, stochastic dominance approach axiomatic approach, fuzzy sets and Alkire-Foster approach.

Dashboards and venn diagram are the simplest methods because these consists merely of a graphical depiction of how the groups of people considered deprived along each dimension. But these measures useful when two to four dimensions are involved and it became inconvenient to examined when more than three dimensions are used.

The stochastic dominance approach is use for the comparison, whether a region or country is or is not explicitly less poor as compare to another with respect to various functional forms and parameters, but it also becomes useless to implement for more than two dimensions.

Statistical approaches like, Principal Component Analysis (PCA) which is most appropriate with continuous normally distributed variables, and Multiple Correspondence Analysis (MCA) which is more appropriate for binary, or categorical variables are used to extract information on the association or correlation between dimensions to reduce; other approaches, like cluster

analysis, classify groups of people who are comparable in terms of their combined deprivations. Statistical analysis is used when overall indices of poverty is calculated, but these approaches of statistical analysis depend on the particular dataset used, and become difficult for cross-country comparisons.

The fuzzy set technique is a powerful method when dealing with the ambiguity of the term poverty. It attempts to discourse two main issues of multidimensional poverty, 1) the identification of a poverty threshold or line 2) the selection of unit of measure as well as for analysis.

The axiomatic approach is basically a list of rules which be followed when studying on multidimensional poverty. For example, Tsui (2002) offers a list of six axioms which are satisfied by unidimensional poverty measures. These axioms are symmetry, monotonicity, invariance, focus, application, continuity and subgroup consistency. This measurement approach of MPI helps to standardize analysis but can also lead to deviations among the approaches.

4.2.1 Alkire and Foster approach:

The existing and more common methodology for the measurement of MPI across the countries is Alkire and Foster methodology. S Alkire and Foster (2007) methodology using a dual-cut-off approach. The first cut-off is used to classify the deprived and non-deprived and second cut-off, is use to separate poor and non-poor, while in the second portion aggregation is performed to find the MPI.

This approach of multidimensional poverty is based on the weighted deprivation score. which are computed using the following equation:

$$P_i = \sum_{k=1}^{K} \omega_k B_{ki} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (4.1)$$

Where vector P_i indicates the deprivation scores of all population and B_{ki} is binary indicator, 1 means deprivation and 0 otherwise. In this approach B_{ki} is the value of component *k of* household *i* and ω_k is the weight of B_{ki}. A household i is recognized as poor if P_i is more than or equal to *k* and will be non-poor, otherwise. Whereas, the headcount ratio is determined by the formula.

$$P_H = \frac{q}{N} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (4.2)$$

where q indicates the number of poor household and n denotes population size. In the next step the average share of weighted indicators which is known as intensity of multidimensional poverty, denoted by A and obtained as follows:

$$A = \frac{\sum_{i=1}^{n} a_i(L)}{N} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (4.3)$$

where $a_i(L)$ is deprivation score. While M_0 indicates the magnitude of multidimensional poverty and is obtained by taking the product of headcount ratio (P_H) and the intensity of the poverty (A).

$$M_0 = \frac{1}{q} \sum_{j=1}^{d} C_i\,(k) \times \frac{q}{N} = P_H \times A \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (4.4)$$

where q indicates the number of poor people and N shows the total sample size.

4.3 Why SEM Instead of Alkire-Foster methodology

In recent years the most common method for the measurement of MPI is Alkire-Foster method. Alkire-Foster methodology is an index-based method and it comprises different indicators, dimensions, and cut-offs for the measurement of MPI. Moreover, it reflects changes in indicators and dimensions of poverty and monitors changes in poverty trends. Therefore, these characteristics of MPI are used as important tools for policy analysis.

The basic difference of Alkire-Foster methodology and SEM is the allocation of weights to indicators of poverty. Basically, Alkire-Foster methodology gives equal weight to the indicators. But, Alkire-Foster methodology is sensitive to the choice of weights for the dimensions and indicators. The magnitude and the intensity of MPI may be different under different weighting schemes. The study of showed that poverty estimates from Alikre-Foster method are quite sensitive to the choice of weights. Whereas, equal weights always underestimate the magnitude of poverty. Therefore, equal weighting scheme is generally criticized by the researchers. Chowdhury and Squire (2006) proved that equal weighting to MPI indicators is "obviously convenient but universally it is considered wrong". For example, if education is more important than health, then the education poverty should not have the same weight as that of the health poverty (Ravallion, 2011). Therefore, the discussion on the technical facets of MPI gives us wider understanding of the issue, and for the selection of such approach which is more robust.

To be able to effectively measure MPI, a large number of factors need to be examined; Their effects both in direct and indirect way need to be taken in consideration; and the measurement to be flexible with both measurement and time error. SEM allows for the incorporation and understanding of multiple relationships within a complicated reality like, MPI. In SEM approach weights assigned on the base of correlation structures among poverty indicators.

Secondly, the use of latent variables (use in this study) is a concept within the area of SEM that permits the researcher to deal with variables which are difficult to evaluate through basic observations. Instead of using the idea of an index of indicators, SEM is able to avoid the errors accumulated from the summation of variables, whether weighted or not. The analysis of variance and covariance between multiple observable indicator variables allows for representation of these latent variables.

4.4 Unit of Measurement

The basic idea of this study is to capture the broader dimensions of poverty such as health, educations and social status of different regions and provinces of Pakistan. Household is considered as unit of measurement.

4.5 Statistical Analysis

Basically, there are four methods of aggregating indicators into MPI. Firstly, allocates equal weights to every indicator, i,e. in the Human Development Index HDI (Filmer & Pritchett, 2001) . .Secondly, weights allocations may be selected on policy makers deliberations or expert opinions (Sabina Alkire & Sumner, 2013). Thirdly, weights can be assigned according to prior information of the data of interest (Barnes & Wright, 2012). Fourthly, statistical techniques are used, like factor analysis and principal component analysis and weights assigned on the basis of correlation structures among poverty indicators (Filmer & Pritchett, 2001; Shaffer, 2013).

In this study statistical technique, SEM is used in both Exploratory Factor Analysis (EFA) style as well as in Confirmatory Factor Analysis (CFA).

4.5.1 Exploratory Factor Analysis (EFA)

EFA is used when the researcher is uncertain as to which factor is described by which indicator, EFA permits the freedom of relationships within the measurement model. The Observed variables in EFA are called indicators and the extracted factors are expected to be the cause for the observed responses. Basically, EFA is based on the common factor model and is represented by the equations.

$$X_1 = \gamma_{11}F_1 + \cdots + \gamma_{1m}F_m + \epsilon_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.5)$$

$$X_2 = \gamma_{21}F_1 + \cdots + \gamma_{2m}F_m + \epsilon_2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.6)$$

•

$$X_p = \gamma_{p1}F_1 + \cdots + \gamma_{pm}F_m + \epsilon_p \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.6)$$

The $\mathbf{F_j}$ show m common factors, the $\boldsymbol{\epsilon_j}$ are the p errors, and the $\boldsymbol{\gamma_{ij}}$ are the p× n factor loadings. The Fj have zero mean and one standard deviation, and are generally assumed to be independent. The $\mathbf{e_i}$ are also independent and the $\mathbf{F_j}$ and $\mathbf{e_i}$ are mutually independent of each other.

In matrix form this can be written as:

$$X_{P\times 1} = X_{P\times n}F_{n\times 1} + \epsilon_{P\times 1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.7)$$

which is equivalent to

$$\Sigma = \mathcal{A}\mathcal{A}^T + cov(e) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.8)$$

where $\Sigma_{p\times p}$ is the correlation matrix of $X_{p\times 1}$. Since the errors are assumed to be independent, cov(e) should be a pxp diagonal matrix. This implies that:

$$var(X_i) = \sum_{j=1}^{m} a^2{}_{ij} + var(e_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.9)$$

The sum of Xi's squared factor loadings is called its communality (the variance it has in common with the other variables through the common factors). The ith error variance is called the specificity of Xi (the variance that is specific to variable i).

The core of exploratory factor analysis is its correlation structure for model indicators. This is obtained by the correlation matrix of the model. The estimation of the model could be obtained through different a method which include maximum likelihood and generalized least squares.

Following the estimation, and to ease interpretation, the factors are transformed into a new set of factors. This process is known as rotation, and comprises on oblique and orthogonal and rotations. The first one requires relaxing the assumption of absence of correlation among factors. Once the factors have a meaningful interpretation, it is possible to obtain person-specific achievement values on the latent variable. The prediction of the achievement/deprivation values could be achieved through several methods that lead to highly correlated but different cardinal values of the factor. In the presence of only cardinal values, factor scores often come from regression analysis and in the presence of binary or categorical variables, factor scores may be computed through Bayesian estimation.

4.5.2 Confirmatory Factor Analysis

It is highly recommended within the literature that once a model is established through EFA, CFA is used with new data to test the model fit. The CFA model further extend to structural model and measurement model specify relationships across factors and between factors and other explanatory variables. CFA in the form of structural model deals with one dimension and its respective indicators; for example, taking education dimension (D_edu) is measured by three indicators. x1 is for "Years of Schooling," and x2 is for "School attendance." According to Weston and Gore Jr (2006), the CFA form in this phenomenon will be.

$$\mathrm{x}^{*1} = \alpha_1 D_{Edu} + e_1 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (4.10)$$

$$\mathrm{x}^{*2} = \alpha_2 D_{Edu} + e_2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (4.11)$$

$$\mathrm{x}^{*3} = \alpha_3 D_{Edu} + e_3 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (4.12)$$

In the above model α_1 **,** α_2 and $\alpha_3$known as regression weights or loadings. This shows the strength of the relationship between the dimension of education and its indicators. e_1 , e_2 and e_3 and are residuals, while x^{*1} , x^{*2} and x^{*3} latent variables.

CFA in the form of measurement model uses for the relationship between all dimensions and measurement variables and the relationship among the dimensions themselves. The MM form was given by Jöreskog et al. (2006).

$$X^* = \tau + \eta £ + e \ldots \ldots (4.13)$$

In the above equation, Ƞ is a loading or regression matrix. X* is the vector of latent variables related. Ʈ is the intercept vector, while e is the residuals. As with EFA, with CFA models one needs to estimate the model, assess its quality of fit, and predict factor scores.

4.6 MPI in the context of SEM

MPI is designed in such a way that maximise discrimination of wealthier and poorer households. This is attained by allocating more weights to those items of poverty which indicate more variability across households. Like, we assume that each household owns a mobile, then mobile would be given zero weight because it would not sufficiently distinguish between poor and rich households. In the same way, if no household were to own a laptop, again the weight would be zero (Steinert et al., 2018). According to this approach, firstly each indicator is assigned a specific weight and after that it summed up. This process produces a continuous scale, and a higher scale score indicate a lower level of poverty because possession or access decreases severity of poverty. The above process can be represented in the following equation.

$$Pi = y_1\, p_{1i} + \cdots + y_k\, p_{ik} + \delta i \ldots \ldots (4.14)$$

where Pi denotes the poverty scale score, p_{ik} the respective poverty indicators, y_k the weights (factor loadings) for each indicator and δ_i a stochastic error term (Sahn & Stifel, 2003).

For the dynamic nature of poverty, Latent Growth Curve Models (LGCMs) will be used. LGCMs have the property to estimate changes over time (Willett & Sayer, 1994).

$$P_{it} = \pi_{0i} + \pi_{1i}(T - T_0)\, t + e_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.15)$$

In the above growth curve model, $\boldsymbol{\pi_{0i}}$ is the parameters of the intercept which will be shown the expected or average value of the poverty in the given time period, $\boldsymbol{\pi_{1i}}$ is the slope parameter which designates change over time, and $\mathbf{e_{it}}$ is the error term which shows the deviation from the expected value

CHAPTER 5

RESULTS AND ANALYSIS

5.1 Analysis

In this study statistical analysis are used in four steps. First of all, find descriptive statistics to find the status of poverty indicators regional wise as well as provincial wise. Secondly, EFA is used to explore the relevant indicators and for the elimination of irrelevant indicators. Thirdly, introduce SEM and used multigroup-comparisons for testing the differences in the concerned measurement model across different regions and provinces. Lastly, use Latent Growth Curve Model (LGCM) for the measurement of growth trajectories of poverty.

5.2 Selection of poverty indicators

For the purpose of this study, we measure poverty in the form of a composite index which aggregates a number of indicators into a scalar score. The basic idea of this study is to move beyond material aspects and analysed the broader dimensions of poverty such as education, health and social capital. Although in different researches the researchers used different kind and number of indicators, but most of these indicators basically cover three main dimensions of MPI. Firstly, housing quality which relate to general health, hygiene and environmental status. Secondly, ownership of assets which have numerous implications as assets can help against economic shocks. Thirdly, human capital which includes health, education, and employment all of which have a range of positive externalities such as health-relevant knowledge, potential for income generation, as well as providing a source of self-respect and fulfilment. In this study we use the indictors in the binary form, for example if household access to a facility, then 1 otherwise 0, Like the same way if a household using a standard and safe source then 1 otherwise 0, For the measurement of poverty in this study we use the following indicators, given in the table (5.1) below. However, a comprehensive overview of the indicators

containing their modalities, categorization and its prior application given in table 1 (given in Appendix A)

Table 5.1 Poverty Indicators Overview

Dimensions	Indicators
Housing quality	occupancy status
	room availability
	main Materials use for floor, walls and roof
	source of lightning
	source of cooking
	sewerage system
	drinking water
	type of toilet facility
Asset ownership	possession of personal agricultural land
	possession of personal non- agricultural land
	possession of livestock
	possession of residential building
	availability of mobile facility
	availability of computer facility
	availability of laptop facility
	availability of Internet facility
Health	health condition
	children immunization
	vaccination
	child mortality
	consultancy for illness
	satisfaction from consultancy
Education	complete primary education
	reason never attends any school/institution
	age at first school registration
	distance of school/institution from home

5.3 Results

5.3.1 Descriptive analysis of household poverty indicators in rural and urban areas in Pakistan

Descriptive statistics is used for the general overview of the poverty indicators status. Table (given in appendix B) shows the poverty indicators, stratified by rural and urban residencies. The results showed that ownership of many assets is notably higher in urban areas. Correspondingly, urban areas have significantly higher standard for living as compared to rural areas in terms of cleanliness and building material used are more sophisticated, However the number of persons living in one room is notably higher in urban households. Moreover, possession of livestock is significantly higher in rural areas as compare to urban areas which may be as indicator of the agriculture dependency in rural areas. Moreover, the accessibility to internet and computer is remarkably higher in urban areas as compared to rural areas. More interestingly the status of nutrition in rural areas are high as compare to urban areas. However, child mortality rate, vaccination facility and other health conditions are almost same in both urban and rural areas. The overview of indicators in rural vs urban areas also shows in the figure below. For the simplicity of diagram taking only those indicators which show more variability examining from table (Given in appendix B).

5.3.2 Descriptive analysis of household poverty indicators provincial-wise

Table (given in Appendix c) shows poverty indicators as provincial wise. The results showed ownership of many assets is remarkably higher in Panjab as compare to other provinces and Baluchistan has worst condition in almost all living and social indicators. Sindh and KPK has almost same conditions in maximum indicators but KPK have higher accessibility to internet and computer facility, availably of rooms and personal agriculture land, however Sindh has slightly higher level in terms of materials use for cooking and sewerage system.

5.3.3 Exploratory Factor Analysis (EFA)

EFA firstly included all indicators (given in table 5.1). EFA is used when the researcher is uncertain as to which factor is described by which indicator, EFA allows for freedom amongst relationships within the measurement model. We examined factor loadings for two time points separately.

5.3.3.1 Data Processing for 2014-15

The basic condition of the data whether or not factor analysis can be used is that the data must have significant correlation. For this, a statistical test name as Bartlett of Sphericity test is use to determine the correlation between the variables. Bartlett test more sensitive in case of large sample data to detect correlations. Another test known as Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO MSA) used to measure the level of intercorrelation to measure the level of intercorrelation between variables and whether or not factor analysis can be carried out. It values vary from 0 to 1. The desired value must be > 0.6 to be able to do Factor Analysis.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.731
Bartlett's Test of Sphericity	Approx. Chi-Square	160019.781
	Df	66
	Sig.	.000

The results revealed that the KMO value is 0.73 so that factor analysis can be carried out. Likewise with the value Bartlett Test with Chi-Squares 160019.781 and significant at 0.000, it can be concluded that the Factor Analysis test can be continued. After The necessary condition fulfilled by the data, EFA applied on the given variables, after a Varimax rotation of the solutions allows us to examined for factors selection.

Table 5.2 Output of rotated Component Matrix

Factor	Indicators
1	possession residential building, occupancy status and room availability
2	standard materials use for walls, roof and floor.
3	possession agricultural land and possession of livestock
4	health condition, child immunization and vaccination.
5	complete primary education, reason for never attend school, age at first school registration

The result of the rotation shows that now the indicators clustered in five factor solution. Indictors of possession residential building, occupancy status and room availability clustered in component 1. Factor 2 clustered on the rotation of indicators of standard materials use for walls, roof and floor. Indicators of possession agricultural land and possession of livestock grouped in factor 3. Factor 4 consist on the indicators of health-related indicators which are health condition, child immunization and vaccination. Education related indicators clustered in factor 5. A number of items had loadings <0.3 So, removing the factors with low factor loadings (possession of non-agriculture land, sources of lighting, cooking, sewerage system, safe drinking water, child mortality, Nutrition, Education Background, Toilet status, Distance of school and Health consultancy) gave the poverty scale with high internal reliability of Cronbach's $\alpha = 0.87$. Complete table of rotated component matrix given (in table 4 appendix D)

5.3.3.2 Data Processing for 2019-20

The assumption that underlies whether or not factor analysis can be used is that the matrix data must have sufficient correlation. Test Bartlett of Sphericity is a statistical test to determine whether there is a correlation between variables.

The results indicate that the KMO value is 0.71 so that factor analysis can be carried out. Likewise with the value Bartlett Test with chi-squares 124560.294 and significant at 0.000, it can be concluded that the factor analysis test can be continued. After these necessary tests, examining rotation matrix for factors selection. The results of EFA given in below table for

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.711
Bartlett's Test of Sphericity`	Approx. Chi-Square	124560.294
	Df	91
	Sig.	.000

Table 5.3 Output of rotated Component Matrix

Factor	**Indicators**
1	standard materials use for walls, roof and floor.
2	possession of internet, mobile and laptop
3	possession agricultural land and possession of livestock
4	health condition, child immunization and vaccination.
5	complete primary education, reason for never attend school, age at first school registration

The result of the rotation nearly same as the result for 2014-15. The indicators clustered in five factor solution. Factor 1 clustered on the rotation of indicators of standard materials use for walls, roof and floor. Factor 2 consist on the group of indicators of modern asset availability, i.e., internet, mobile and laptop. Indicators of possession agricultural land and possession of livestock grouped in factor 3. Factor 4 consist on the indicators of health-related indicators which are health condition, child immunization and vaccination. Education related indicators

clustered in factor 5. Removing the factor with low factor loading give higher value of Cronbach's α = 0.86. Complete table of rotated Component Matrix given (in table 5 appendix D)

5.3.4 SEM

It is highly recommended within the literature that once a model is established through EFA, CFA is used with new data to test the model fit. Applying SEM in the form of CFA and by analysing multiple group comparisons for the measurement of MPI region-wise as well as across difference provinces to examine cross-geographical validity. For this, following the procedural steps suggested by Steenkamp (1998). Table 5.7 displays the model fit for all three types of invariances tests. Configural invariance, the model with the fewest constraints had a CFI of 0.83 and 0.80 for 2014-15 and 2019-20 respectively and thus did not display acceptable fit. By applying the second test of metric invariance model again weaker for both time points with CFI 0.76 and 0.70 for 2014-15 and 2019-20 respectively and almost same result given by scalar invariance. These findings indicate difference in the meaning of poverty between urban and rural as well as provincial wise households. So, the validity and reliability of the recommended poverty indicators could not be confirmed across the rural vs urban as well as across different provinces.

Table 5.4 Goodness of Fit Indices

2014-15			
Model	**CFI**	**RMSEA**	**SRMR**
Configural Invariance	0.83	0.07	0.06
Matric Invariance	0.76	0.08	0.09
Scalar Invariance	0.00	0.17	0.28
2019-20			
Configural Invariance	0.80	0.06	0.05
Matric Invariance	0.71	0.07	0.05
Scalar Invariance	0.00	0.17	0.28

Authors computation

Lastly, constraints are put on kind and number of indicators used, however loadings are not taken equal which gave best fit model having Confirmatory Fit Index (CFI) = 0.96, Tucker-Lewis's index (TLI) = 0.95 and Root Mean Squared Error of Approximation (RMSEA) 0.03 for 2014-15 and Confirmatory Fit Index (CFI) = 0.97, Tucker-Lewis's index (TLI) = 0.95 and Root Mean Squared Error of Approximation (RMSEA) 0.02 for 2019-20. The results indicates that each sub-population consider respective items of population differently.

5.3.5 Multiple-group SEM for 2014-15

Multiple-group comparisons for the model with the most acceptable fit to analyse the MPI region-wise as well as for the provincial-wise. The results reveals that a considerable number of poverty items could distinguish adequately between poorer and wealthier households in one area, but were found to have little relevance to socioeconomic status in the other area.

5.3.5.1 Rural vs Urban sub-populations Comparison

The findings drawn considerably different as we look it is as rural vs urban areas. Different regions give different relevance to same indicator of poverty. For example, the indicators related to possession agricultural land and possession of livestock highly relevant to rural households because agriculture is the primary occupation in villages where people live in proximity of their lands and this character of poverty would also be impacted more in rural areas due to variability in this indicator. Moreover, houses occupancy and room availability also appear of higher relevance in rural households as compare to urban households as the basic aim of the poor people in rural areas that they have their own house, so that why these indicators are more prominent in rural areas. While on the other side, a range of choices available in urban areas for the materials used in house construction and design of houses so that why the indicators related to standard materials used for floor and walls turn out are more weighted in urban households as compare to rural households.

Besides these differences there are some other dimensions and indicators of poverty which are equally weighted by both rural as well as urban households and they equally contribute to poverty measurement in both situations like, indicators related to health (child immunization, vaccination and health condition) and education (reason for never attend school, Complete primary education, age at first registration) are equally valued both in rural vs urban areas.

Table 5.5 Multiple-group SEM for urban and rural sub-populations

Indicators	**Rural**	**Urban**
	Standardized factor loading	Standardized factor loading
having residential building (comp. / under construction)	0.24***	0.46***
own occupied house	0.82***	0.25***
room availability	0.72***	0.45***
standard material is used for walls	0.61***	0.79***
standard material is used for roof	0.60***	0.76***
standard material is used for roof	0. 58**	0.64***
having livestock in personal possession	0.33***	0.017
having personal agricultural land	0.93***	0.01
children immunization	0.87***	0.87***
Vaccination	0.86***	0.92***
health condition	0.98***	0.99***
complete primary education	0.40***	0.38***
reason for never attend any school/institution	0.80***	0.85***
reason for never attend any school/institution	0.80***	0.85***

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

5.3.5.2 Inter-provincial sub-populations Comparison

Like for region-wise the findings drawn for inter-provincial comparison also considerably different. Like the indicators of occupancy status, residential building, possession of livestock and agricultural land are insignificant for Sindh and Baluchistan. The results strongly suggest that each province assigns different importance to respective items. The results revealed the province of KPK gave high weighted to the indicators of occupancy, standard materials use for walls and indicators of education (complete primary education and age at first registration). The household of Panjab give high weight to the indicators of possession of agricultural land and personal livestock and this may be the agricultural geography of Panjab.

Besides these differences the indicators related to health to almost equally weighted by all provinces which indicate that the health dimension is equally important for all the provinces.

Table 5.6 Multiple-group SEM for provincial-wise sub-population

Indicators	KPK	Panjab	Sindh	Baluchistan
having residential building (comp. / under construction)	0.26***	0.295***	0.01	0.02
own occupied house	0.72***	0.60***	0.03	0.01
room availability	0.62***	0.50***	0.67***	0.41***
standard material is used for walls	0.92***	0.76***	0.80***	0.67***
standard material is used for roof	0.63***	0.85***	0.91***	0.86***
standard material is used for roof	0.59***	0.75***	0.78***	0.85***
having livestock in personal possession	0.64***	0.69***	0.02	0.10
having personal agricultural land	0.67***	0.665***	0.04	0.05
children immunization	0.84***	0.84***	0.90***	0.97***
Vaccination	0.91***	0.85***	0.88***	0.79***
health condition	0.98***	0.97***	0.99***	0.96***
complete primary education	0.95***	0.63***	0.18***	0.41***
reason for never attend any school/institution	0.60***	0.58***	0.81***	0.97***
age at first school registration	0.85***	0.63***	0.38***	0.41**

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

5.3.6 Multiple-group SEM for 2019-20

Multiple-group comparisons for the model with the most acceptable fit for 2019-20 to analyse the MPI region-wise as well as for the provincial-wise. The results are nearly same as the results of 2014-15. But in this time point some new indicators are included and some excluded as compare to the indicators of previous time. The result shows a considerable number of poverty items could distinguish adequately between poorer and wealthier households in one area, but were found to have little relevance to socioeconomic status in the other area.

5.3.6.1 Rural vs Urban sub-populations Comparison

The findings drawn from the data set of 2019-20 also shows considerably different as we look it is as region. But in this year standard materials used for floor and walls are equally weighted by both urban as well as rural households. The weights for child immunization, vaccination and health condition are equally valued both in rural vs urban areas which is align with the results of 2014-15. However, in this time point the indicators of occupancy status and the possession of residential building are completely absent due to show low factor loadings in exploratory factor analysis and dropped. In this time point some new indicators like availability of internet and laptop facility and highly weighted by urban as compare to rural household. Interestingly, in this time period the indicators related to education are equally weighted by rural vs urban household. The results revealed that at passage of time the relevance of poverty indicators change, and the most relevant indicators of one time period become totally irrelevant for the other time period and same conclusion can be drawn for different regions. The results are given in the table below.

Table 5.7 Multiple-group SEM for urban and rural sub-populations

	Rural	**Urban**
Indicators	Standardized factor loading	Standardized factor loading
Indicators	Rural	Urban
standard material is used for floor	0.66***	0.66***
standard material is used for roof	0.79***	0.74***
standard material is used for walls	0.74**	0.69**
availability of internet facility	0.45***	0.64***
availability laptop facility	0.50***	0.65***
availability of mobile facility	0.40***	0.35***
having livestock in personal possession	0.43***	0.015
having personal agricultural land	0.83***	0.02
health condition	0.99***	0.98***
Vaccination	0.84***	0.85***
children immunization	0.86***	0.84***
reason for never attend any school/institution	0.95***	0.94***
complete primary education	0.96***	0.96***
age at first school registration	0.55**	0.36*

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

5.3.6.2 Inter-provincial sub-populations Comparison

The results of multiple-group SEM for provincial-wise sub-populations given in table 5.8. Like for region-wise the findings drawn for inter-provincial comparison also considerably different. The results revealed that the provinces of Sindh and Baluchistan which gave relatively less weight to indicators of standard materials use for the construction of house like standard materials use for walls, roof and floor in the previous time, gave high weight in this time point which indicate that the standard and life style variation for these provinces. It also confirms the assumption that an indicator of poverty can never be consider equally at passage of time. The

households of KPK give high weight to the access of new assets availability, like the availability of mobile, laptop and computer and the status for the remaining indicators is almost same as in previous time. Moreover, the results of the indicators related to health is aligned to the previous time that is this dimension is almost equally weighted by all provinces which indicate that the health dimension is equally important for all the provinces. The indicators of education dimension are highly weighted in the province of KPK followed by Panjab, Sindh and Baluchistan. The results strongly suggest that each sub-population assigns different importance to respective items.

Table 5.8 Multiple-group SEM for provincial-wise sub-population

Indicators	**KPK**	**Panjab**	**Sindh**	**Baluchistan**
standard material is used for floor	0.72***	0.63***	0.81***	0.72***
standard material is used for roof	0.76***	0.57***	0.90*	0.80***
standard material is used for walls	0.53***	0.64***	0.83***	0.72***
availability of Internet facility	0.48***	0.62***	0.71***	0.61***
availability laptop facility	0.62***	0.52***	0.44***	0.41***
availability of mobile facility	0.52***	0.42***	0.40***	0.45***
having livestock in personal possession	0.64***	0.69***	0.58***	0.50***
having personal agricultural land	0.67***	0.665***	0.03	0.46***
health condition	0.99***	0.99***	0.96***	0.96***
Vaccination	0.95***	0.81***	0.77***	0.84***
children immunization	0.88***	0.84***	0.85***	0.91***
reason for never attend any school/institution	0.97***	0.97***	0.84***	0.94***
complete primary education	0.95***	0.94***	0.98***	0.99***
age at first school registration	0.552**	0.427**	0.382***	0.290**

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

5.3.7 Average poverty level and changes over time

By taking the average of MPI. The results revealed that the average poverty level in rural areas is higher as compare to poverty level in urban areas (Higher score shows lower level of poverty). Comparatively, Panjab has less poverty level as compare to other provinces. The situation of Baluchistan is worst as compare to the remaining provinces. The results indicate that the level of poverty reduced over time, but the reduction level is different for the different regions and provinces. The reduction in the poverty level in the urban areas is greater than as compare to rural areas and the same situation for Panjab and KPK as compare to Sindh and Baluchistan.

Table 5.9 Average Poverty Level and changes over time

	2014-15	2019-20	Change
Rural	2.03	2.44	-0.29
Urban	3.75	3.90	-0.43
KPK	2.21	3.12	-0.28
Panjab	2.45	3.94	-0.45
Sindh	1.71	1.81	-0.19
Baluchistan	0.74	1.02	-0.22
Overall	3.34	3.65	-0.40

After taking the average level of poverty, find percentage of households who live under this average level and compare the results with the results of existing method of Alkire-Foster of the measurement of poverty.

5.3.8 Comparison of the Results with existing approach

By comparison of the finding of two different approaches for the measurement of MPI, the results revealed that the Alkire-Foster methodology under-estimate the magnitude of MPI. These results are aligned with the study of Khan and Akram (2018) which proved that equal weighting scheme has underestimated the magnitude of multidimensional poverty at all levels.

Therefore, these findings suggest that weights play an important role in the estimation of poverty and the estimates of MPI are quite sensitive to the weighting scheme Belhadj (2012). It implies that multidimensional poverty in Pakistan is highly sensitive to the weights of dimension and indicators. The researchers argue that important dimensions of poverty should have higher weight as compared to the other dimensions (Ravallion, 2011).

Table 5.10 Estimates of MPI with Alkire-Foster method and SEM

(PSLM 2014-15)

MPI	Alkire and Foster Method	SEM Method
Rural	53.6%	54.4%
Urban	9.4%	12.3%
KPK	49.1%	51.4%
Panjab	31.5%	35.5%
Sindh	43.2%	47.3%
Baluchistan	71%	73.5%
Overall	38.8%	42.4%

CHAPTER 6

CONCLUSIONS

The measurement method we use in this study is almost similar to other measurement methods used in literature for the measurement of composite poverty index. But the results of this study revealed that the poverty index did not show cross-geographical validity. In other words, it is stated that poverty consider differently in different regions and provinces of Pakistan.

The results of the study revealed that each group of population assigns a specific value to a certain indicator of poverty which is use as its weigh for the aggregation of poverty scale score. These weights vary in each subsection of population so the scale score which is derived on the basis of these scores by using mathematical process is also different for different populations. The finding of the study revealed that the comparison and ranking of household use in the previous studies could be less reliable. Its means that the concept and meaning of poverty in different regions and provinces is different. For instant a range of indicators of poverty such as possession of agriculture land, Possession of livestock, occupancy of house, possession of residential building, technological advancement and health status could distinguish significantly between wealthier and poorer households in one region or province, but show insignificant relevance in the other region or province. So, the equivalency of a unique measurement model might not be confirmed across sub groups of population. Based on the results of the study poverty rankings based on one measurement construct would be led to measurement error.

According to this study the poverty level in rural areas is more than as compare to urban areas. This is in line with a number of previous studies. The results of this study are somewhat similar to descriptive statistics to other studies, but in this study a number of indicators like possession of house, possession of agricultural land and possession of livestock availability rooms and

education attainment represented rural households on average as 'better off'. Therefore, by finding the higher deprivation of rural areas may indeed have some validity, but the selection of indictors may be biased against rural population (Booysen et al., 2007). As in conventional composite poverty index measurement a number of indicators like land ownership or agricultural assets which are more strongly valued in rural population are generally absent (Batana, 2013; Vyas & Kumaranayake, 2006). Therefore, poverty in rural households may be really higher, but the indicators use in the measurement of poverty may also be biased against rural population which overestimate these differences and the same situation may be exist for provincial wise too. The results of the study revealed that for the accurate measurement of poverty, it is necessary to first find the relevant indicators of poverty for each subgroup and then assign the weights according to the population relevance.

In this study we estimate a composite poverty index for Pakistan overall and across its urban and rural as well as across its different provinces. The results of the study revealed that the poverty level in rural areas is slightly higher in 2014-15 and 2019-20 (higher scale score shows higher level of poverty). By comparing the poverty level in provincial wise Panjab has least level of poverty on all time points, and Baluchistan has worst situation as compare to the rest of provinces, the situation of Sindh is also critical. For the observation of change over time in MPI we use latent growth model. The results revealed that there is reduction of poverty observed over time, but the reduction level vary for the different regions and provinces.

6.1 Policy Recommendations

- The study concludes that the measurement of poverty is complex phenomenon in Pakistan and it is quite sensitive to the choice of weights. So, the researcher should be

careful about the choice of weighting scheme while providing estimates of multidimensional poverty.

- Policy makers should observe the poverty figures and trends and use a robust model for the measurement of poverty and for identification of poor group and region in the country and then continuously check their wellbeing.
- The main objective of the policy makers should be on the reduction of poverty. In that case, similar policies for all regions and provinces will not help to achieve this objective. Therefore, the deprived regions of the country should be focused separately to target poverty and regional allocation of resources should also be made according to the nature of poverty like the govt should provide access to modern and economic assets and construction materials to improve the living standard of urban population, while on the other side actions should be taken for the improvement of agricultural and livestock in rural areas to overcome poverty.
- Policies should be designed in such a way that the beneficiaries of the program can eventually come out from the poverty circle and no long rely on govt support.
- The existing Programs for poverty alleviation can be improve through govt-private

6.2 Limitations of the study

This study has a number of limitations. Some assets can become more accessible and common over time (e.g., Internet and phones) and might thus become less significant for categorizing wealthier and poorer households. So, a ‘standard size’ poverty index would be subject to measurement bias as assigned weights would differ between one time point and the other. Second limitation lies in the binary nature of poverty indicators. That is, the aggregated index captures ownership of a certain asset, but not necessarily their quality, functionality, and possible depreciation over time. Thirdly, poverty indicators were measured at a household

rather than individual level. Hence, there was no information on potential intra-household inequalities such as in education or nutrition. Specifically, there might be significant differences in resource distributions between female and male household members that could point to important gender gaps in a society. Further, we have tested validity in a very specific population and cannot claim generalizability of our findings.

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Appendix A

Table 1: Poverty indicators: overview

Indicators	**Modalities of the variables**	**Categorization**	**Prior application**
Present occupancy status	1. Owner occupied (not self-hired) 2. Owner occupied (self-hired) 3.On rent 4. Subsidized rent 5.Rent free	(If Household Own Occupied then 1, otherwise 0) So, 1,2 =1 3,4,5=0	Mahmood and Hussain (2020), (Khan et al., 2014)
Room availibilty		(If a room available for tree or less than three persons then 0, otherwise 1)	(Galobardes et al., 2006), (Cerioli & Zani, 1990),
Main material is used for roof	1. RCC/RBC 2. Wood/Bamboo 3. Iron/Cement sheets 4. Metal/Tin/Girders/T-Iron 5. Other	(If household has safe and durable roof then 1, otherwise 0) So, 1,3,4=1 2,5=0	Ningaye (2011), Pinilla-Roncancio et al. (2020), Idrees and Baig (2017)
Main material is used for Floor	1. Earth/Sand 2. Dung 3. Ceramic tiles/Marbles/Chips 4. Parquet or polished wood 5. Cement 6. Brick floor 7. Other	(If Household use advance material for floor, then 1, otherwise 0) So, 3,4, 5,6,7=1 1,2=0	Ningaye (2011), Pinilla-Roncancio et al. (2020),
Main material is used for walls	1. Burned bricks/block 2. Raw bricks/mud 3. Wood/bamboo 4. Plywood/Cardboard 5. Stone 6. Other (Please explain)	(If Household use durable material, then 1, otherwise 0) So, 2,3,4=0 1,5,6=1	Ningaye (2011), Pinilla-Roncancio et al. (2020), Idrees and Baig (2017)

Personal agricultural land	1. yes 2. no	(If Household has any agricultural land, then 1, otherwise 0)	(Moene, 1992), (Finan et al., 2005)
Non-agriculture land, property or plot in personal possession	1. yes 2. no	(If Household has any non-agricultural land, property or plot in personal possession, then 1, otherwise 0)	(Moene, 1992), (Finan et al., 2005)
Residential Building (Comp. / under construction)	1. yes 2. no	(If Household has any Residential Building, then 1, otherwise 0)	(Zhu et al., 2018),
Livestock in personal possession	1. yes 2. no	(If Household has any Livestock, then 1, otherwise 0)	(Alary et al., 2011), (Herrero et al., 2016), (Alary et al., 2011)
Main fuel used for lighting	1. Electricity 2. Solar Energy 3. Gas 4. Kerosene oil\Diesel\Petrol 5. Fire Wood 6. Candle 7. Others	(If Household use Safe and modern mean of lighting then 1, otherwise 0) So, 1,2,3=1 4,5,6,7=0	Ningaye (2011), Gao and Sun (2020)
Main fuel used for cooking	1. Fire-wood 2. Gas 3. LPG 4. Kerosene oil 5. Electricity 6. Dung cake 7. Crop residue 8. Charcoal\Coal 9. Other	(If Household use Modern/environment friendly mean of Fuel, then 1, otherwise 0) So, 2,3,4,5=1 1,6,7,8,9=0	Ningaye (2011), Gao and Sun (2020), Rogan (2016), Nogales, and Suppa (2020)
Toilet status	1. Facility not available 2. Flush system (linked to sewerage) 3. Flush (linked to Septic tank) 4. Flush (connected to open drain) 5. Dry raised latrine 6. Pit latrine	(If a household has not toilet facility, then 0, otherwise 1) So, 1,7=0 2,3,4,5,6,7=1	(Karpati et al., 2020), (Asselin, 2009), (Yu, 2013)

	7. Other		
Sewerage System	1. Underground drains 2. Covered drains 3. Open drain 4. No system	(If household has safe drainage system, then 1, otherwise 0) So, 1, 2=1 3,4 = 0	Mahmood and Hussain (2020), Rogan (2016), Nogales, and Suppa (2020)
Main source of drinking water for the household	1. Piped water 2. Hand pump 3. Bore Hole (Motor Pump) /Tube Well 4. Closed well 5. Open well 6. Protected Spring 7. Un protected Spring 8. Others	(If Household use Safe and healthy source of water then 1, otherwise 0) So, 1,2,3,4=1 5,6,7,8=0	Ashaal and Bakri (2019), Pinilla-Roncancio et al. (2020), Rogan (2016), Nogales, and Suppa (2020)
Internet facility	1. yes 2. no	If Household has the facility of Internet, then 1, otherwise 0)	Hidayat et al. (2021); Idrees and Baig (2017)
Mobile facility	1. yes 2. no	If Household has the facility of mobile then 1, otherwise 0)	Ningaye (2011)
Computer facility	1. yes 2. no	If Household has the facility of computer, then 1, otherwise 0)	(Vollmer & Alkire, 2018), (Oyelaran-Oyeyinka, 2014)
Laptop facility	1. yes 2. no	If Household has the facility of laptop, then 1, otherwise 0)	(Vollmer & Alkire, 2018), (Oyelaran-Oyeyinka, 2014)
Eeducational background	1. Never attended school/institution 2. Attended school/ Institution in the past 3. Currently attending school/institution	(If even a single member never attends School/institution then 0, otherwise 1) So, 1=0 2,3 =1	Gao and Sun (2020), Rogan (2016), Nogales, and Suppa (2020)
Age at first school registration	1. =>6 years <6 years	If a child is not regester in school at age years 6 then 0, otherwise 1	Ningaye (2011)

Years of schooling	1. No household member aged 10 years or older has completed five years of schooling. 2. At least one household member aged 10 years or older has completed five years of schooling.	(If No household member aged 10 years or older has completed five years of schooling then 0, otherwise 1) So, 1=0 2=1	Idrees and Baig (2017), Nogales, and Suppa (2020), Gao and Sun (2020)
Distance of school/institution from home	1. 0-2km 2. 2-5km 3. 5-10km 4. 10-20km 5. Above 20km 6. Don't know 7. Hostel	(If the distance of school/institution from home is 10km or less then 1, otherwise 0) So, 1,2,3,4=1 5,6,7= 0	(Schreiner, 2016), Ningaye (2011)
Reason for never attend any school/institution	1.Too expensive 2. Too far away 3. Poor teaching / behavior 4. Had to help at home 5. Had to help with work 6. Parents/elders did not allow 7. No female staff 8. No male staff 9. Child sick/handicapped 10. Child too young 11. Child not willing 12. Lack of documents 17. Other (specify …….)	(If a member of Household leave education due to financial issues, then 0, otherwise 1) So, 1,2,4,5,7,8=0 3,6,9,10,11,12,17=1	(Schreiner, 2016), Ningaye (2011)
Child mortality	1. If in the family any child in the age of 0-5 has not died 2. If in the family any child in the age of 0-5 has died	(If a family any child in the age of 0-5 has died then 0, otherwise 1) So, 1=0 2=1	Ashaal and Bakri (2019), Mahmood and Hussain (2020), Rogan (2016), Nogales, and Suppa (2020)
Nutrition	1. Any adult under 70 years of age or any child do not undernourish. 2. Any adult under 70 years of age or any child undernourished	(If any adult under 70 years of age or any child undernourished then 0, otherwise 1) So, 1=1 2=0	Ashaal and Bakri (2019), Mahmood and Hussain (2020), Rogan (2016), Sabina Alkire et al. (2020)

Health Condition (Was he/she sick or injured during the last two weeks?)	1. yes 2. no	(If a member of a household became sick/injured from last three months then 0, otherwise 1)	(Iqbal & Nawaz, 2017), (Craig et al., 2008)
Consultancy for illness (Did consult anyone for this illness?)	1. yes 2. no	(If a member of household consult anyone for his/her illness then 1, otherwise 0)	(Sen, 1985)
Satisfaction from health service consultant	1. Satisfied 2. Doctor not presents 3. Staff non-cooperative 4. Lady Staff not present 5. Lack of cleanliness 6. Long wait 7. Costly treatment 8. Staff untrained 9. Medicines not available 10. Unsuccessful treatment 11. Other	(If a member of Household is satisfied from the health consultancy provided then 1, otherwise 0) So, 1=1 2,3,4,5,6,7,8,9,10,11=0	Mahmood and Hussain (2020), Rogan (2016), Nogales, and Suppa (2020)
Visit to health unit (Has any member of the household visited the health unit during the last 30 days?)	1. yes 2. no	(If any member of the household visited the health unit during the last 30 days, then 0, otherwise 1)	
Children Immunization and vaccination	1. Child has been immunized 2. Child has not been immunized 3. Don't know Vaccination 1. BCG 2. PENTA 3. POLIO MEASLES	(If every child in a house has been immunized then 1, otherwise 0)	(Klasen, 2008), (Grosse et al., 2008)

Appendix B

Table 2: Household poverty in urban and rural in Pakistan

	2014-15		2019-20	
Indicators	Rural	Urban	Rural	Urban
1. Own Occupied house	91.5%	79.2%	89.1%	70.8%
2. Room available for more than three persons	32.0%	36.3%	34.8%	39.1%
3. Standard material is used for roof	52.4%	84.0%	62.7%	91.3%
4. Standard material is used for Floor	52.4%	84.0%	44.2%	87.9%
5. Standard material is used for walls	56.8%	90.9%	72.6%	95.4%
6. Having Personal agricultural land	40.9%	9.6%	37.1%	7.0%
7. Having Non-agriculture land, property or plot in personal possession	2.7%	5.0%	3.2%	4.7%
8. Having Residential Building (Comp. / under construction)	91.0%	79.2%	75.0%	64.4%
9. Having Livestock in personal possession	51.2%	6.8%	42.6%	5.3%
10. Standard fuel used for lighting	86.9%	99.1%	93.7%	99.2%
11. Standard fuel used for cooking	10.2%	72.2%	22.6%	86.0%
12. Standard Toilet	74.2%	98.2%	83.1%	98.2%
13. Standard Sewerage System	4.2%	50.2%	6.9%	58.5%
14. Safe source of drinking water for the household	80.2%	86.7%	66.7%	63.9%
15. Availability of Internet facility	18.6%	43.6%	23.4%	46.5%
16. Availability Mobile facility	86.6%	94.6%	91.2%	96.1%
17. Availability Computer facility	4.4%	17.7%	4.2%	9.7%

18. Availability Laptop facility	4.4%	17.7%	3.8%	11.4%
19. Reason for never attend any school/institution	46.2%	69.6%	61.4%	63.8%
20. .Complete primary education	64.5%	77.8%	74.0%	76.5%
21. Child mortality (No child has died in last year)	73.5%	77.8%	77.9%	82.3%
22. Nutrition (Able to take balance diet)	37.5%	22.5%	38.7%	29.6%
23. Health Condition (Was he/she is not sick or injured during the last two weeks?)	94.4%	92.7%	91.9%	90.2%
24. Consultancy for illness (Did consult anyone for this illness?)	88.7%	95.5%	92.7%	90.8%
25. Visit to health unit (Has any member of the household not visited the health unit during the last 30 days?)	95.6%	96.2%	89.6%	92.7%
26. Vaccination	96.4%	97.7%	96.4%	97.6%
27. Children Immunization	97.5%	98.1%	97.5%	97.8%

Appendix C

Table 3: Household poverty in provinces of Pakistan

Indicators	KPK		PANJAB		SINDH		BALOCHISTAN	
1. Own Occupied house	**2014-15**	**2019-20**	**2014-15**	**2019-20**	**2014-15**	**2019-20**	**2014-15**	**2019-20**
	88.4%	85.0%	88.4%	85.0%	89.8%	77.4%	92.6%	86.7%
2. Room available for three or less than three persons	47.0%	47.9%	34.5%	38.2%	14.6%	21.1%	41.3%	39.9%
3. Standard material is used for roof	51.8%	60.3%	76.6%	86.3%	45.7%	66.0%	21.8%	29.1%
4. Standard material is used for Floor	45.5%	39.0%	72.5%	71.9%	49.4%	56.2%	30.5%	23.4%
5. Standard material is used for walls	51.3%	79.8%	85.9%	92.5%	50.4%	71.5%	18.4%	32.6%

6.	Having Personal agricultural land	41.3%	33.0%	37.8%	27.6%	22.0%	21.1%	5.6%	4.2%
7.	Having Non-agriculture land, property or plot in personal possession	1.7%	2.5%	4.1%	4.1%	1.8%	1.3%	4.5%	2.9%
8.	Having Residential Building (Comp. / under construction)	88.4%	87.3%	88.6%	86.7%	90.4%	88.3%	88.4%	86.4%
9.	Having Livestock in personal possession	45.6%	36.4%	45.7%	31.3%	34.3%	47%	29.5%	60%
10.	Standard fuel used for lighting	93.9%	97.3%	93.4%	98.2%	84.7%	91.1%	75.5%	96.0%
11.	Standard fuel used for cooking	16.1%	28.0%	24.1%	46.3%	25.2%	51.7%	10.2%	25.7%
12.	Standard Toilet	82.6%	86.8%	75.9%	89.7%	82.4%	89.0%	74.9%	76.2%

13. Standard Sewerage System	7.5%	4.9%	23.45%	26.2%	27.5%	36.0%	10.5%	7.7%
14. Safe source of drinking water for the household	67.3%	64.3%	93.9%	68.1%	83.5%	70.6%	51.0%	45.2%
15. Availability of Internet facility	34.5%	42.7%	29.8%	32.7%	28.4%	29.3%	18.4%	20.5%
16. Availability Mobile facility	94.5%	94.7%	90.8%	93.6%	84.4%	89.9%	76.4%	91.2%
17. Availability Computer facility	10.3%	7.2%	8.1%	6.6%	4.2%	5.4%	2.5%	1.4%
18. Availability Laptop facility	10.3%	7.2%	8.1%	6.9%	4.2%	4.9%	2.5%	3.1%
19. Having Eeducational background	42.5%	64.4%	54.6%	68.6%	51.2%	62.3%	43.7%	40.3%
20. Complete primary education	73.7%	82.5%	68.0%	74.4%	64.1%	75.4%	67.1%	74.3%

21. Child mortality (No child has died in last year)	80.3%	82.7%	75.9%	74.5%	76.7%	77.5%	84.1%	83.4%
22. Nutrition (Able to take balance diet)	45.7%	40.3%	23.4%	33.4%	42.4%	41.3%	34.1%	45.4%
23. Health Condition (Was he/she is not sick or injured during the last two weeks?)	92.0%	9 90.0%	93.1%	91.1%	96.4%	91.7%	96.0%	94.4%
24. Consultancy for illness (Did consult anyone for this illness?)	85.7%	85.7%	89.4%	90.4%	97.7%	95.6%	83.0%	90.4%
1. Vaccination	96.4%	98.7%	97.7%	97.7%	95.7%	93.9%	98.01%	97.4%
25. Children Immunization	97.5%	97.9%	98.4%	98.0%	98.4%	97.8%	93.7%	94.9%

Appendix (D)

Table 4 Rotated Component Matrix 2014-15

Components					
Indicators	1	2	3	4	5
Having Residential Building (Comp. / under construction)	0.789				
Own Occupied house	0.604				
Room availability	0.54				
Standard material is used for walls		0.730			
Standard material is used for roof		0.520			
Standard material is used for floor		0.656			
Having Livestock in personal possession			0.810		
Having Personal agricultural land			0.813		
Children Immunization				0.508	
Vaccination				0.614	
Health Condition				0.780	
Complete primary education					0.697

Reason ever attends any school/institution					0.730
Age at first school registration					0.54

Table 5 Rotated Component Matrix 2019-20

Components					
Standard material is used for floor		0.756			
Standard material is used for roof		0.766			
Standard material is used for walls		0.713			
Availability of Internet facility				0.500	
Availability Laptop facility				0.783	
Availability of Mobile Facility				0.65	
Having Personal agricultural land			0.757		
Having Livestock in personal possession			0.710		
Health Condition	0.474				
Vaccination	0.713				
Children Immunization	0.606				
Complete primary education					0.727
Reason never attends any school/institution					0.593
Age at first school registration					0.345