ESSAYS ON SOCIAL SAFETY NETS

By

Muhammad Mujahid Iqbal

PIDE2016FPHDECO10

Supervisor:

Dr. Nasir Iqbal

Associate Professor, PIDE, Islamabad

Co-Supervisor:

Dr. Saima Nawaz

Assistant Professor, COMSATS University, Islamabad

PIDE School of Economics

Pakistan Institute of Development Economics,

Islamabad

2022

ESSAYS ON SOCIAL SAFETY NETS

By

Muhammad Mujahid Iqbal

PIDE2016FPHDECO10

Supervisor:

Dr. Nasir Iqbal

Associate Professor, PIDE, Islamabad

Co-Supervisor:

Dr. Saima Nawaz

Assistant Professor, COMSATS University, Islamabad

A dissertation is submitted to PIDE School of Economics,

in partial fulfillment of the requirements for the Degree of Doctor of Philosophy (PhD) in Economics.

PIDE School of Economics

Pakistan Institute of Development Economics,

Islamabad

2022

Certificate of Approval

This is to certify that the research work presented in this thesis, entitled: **"Essays on Social Safety Nets"** was conducted by **Mr. Muhammad Mujahid Iqbal** under the supervision of **Dr. Nasir Iqbal** and **Dr. Saima Nawaz**. No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics from **Pakistan Institute of Development Economics, Islamabad.**

Student Name: Mr. Muhammad Mujahid Iqbal Signature: ____________
PIDE2016FPHDECO10

Examination Committee:

a) **External Examiner: Dr. Abdul Sattar** Signature: ____________
Professor,
Bahria University Islamabad.

b) **Internal Examiner: Dr. Muhammad Jehangir Khan** Signature: ____________
Assistant Professor
PIDE, Islamabad

Supervisor: Dr. Nasir Iqbal Signature: ____________
Associate Professor
PIDE, Islamabad

Co-Supervisor: Dr. Saima Nawaz Signature: ____________
Assistant Professor
COMSATS, Islamabad

Dr. Shujaat Farooq Signature: ____________
Head, PIDE School of Economics (PSE)
PIDE, Islamabad

Author's Declaration

I Mr. Muhammad Mujahid Iqbal hereby state that my PhD thesis titled **"Essays on Social Safety Nets"** is my own work and has not been submitted previously by me for taking any degree from **Pakistan Institute of Development Economics, Islamabad'** or anywhere else in the country/world.

At any time if my statement is found to be incorrect even after my Graduation the university has the right to withdraw my PhD degree.

Mr. Muhammad Mujahid Iqbal

PIDE2016FPHDECO10

Plagiarism Undertaking

I solemnly declare that research work presented in the thesis titled **"Essays on Social Safety Nets"** is solely my research work with no significant contribution from any other person. Small contribution/help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the **HEC** and **Pakistan Institute of Development Economics, Islamabad** towards plagiarism. Therefore I as an Author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of PhD degree, the University reserves the rights to withdraw/revoke my PhD degree and that HEC and the University has the right to publish my name on the HEC/University Website on which names of students are placed who submitted plagiarized thesis.

Students/Author Signature:____________________

Mr. Muhammad Mujahid Iqbal

PIDE2016FPHDECO10

I dedicate this dissertation to my late mother and late sister.

Acknowledgement

I express my profound thanks to Almighty Allah, who granted me courage, determination and potential to undertake and accomplish this piece of applied research work. As a matter of fact, it was not possible for me to perform this difficult task without His blessings and help. So, I am indebted to Him from the core of my heart.

It is hard to overstate my gratitude to my Ph.D. Supervisor Dr. Nasir Iqbal, without his inspirational guidance, enthusiasm, encouragements, his thought-provoking criticism, I could never have finished my research work. For me, he is not only my teacher, but also my lifetime mentor and advisor. I, once again, express my heartfelt gratitude to him and pray for his health and services for the nation, as well as for the noble profession. I am also thankful to my co-supervisor Dr. Saima Nawaz for her support and guidance throughout my research work.

I am also thankful to all Heads of Department and Deans during PhD for their guidance and input to improve the quality of research.

I am thankful to all the professors and teachers who have taught me during the course of my degree at PIDE, as well as the countless teachers who have helped shape my academic career. I pay special thanks to Dr. Shujaat Farooq, Dr. Abdul Jalil and Dr. Jahangir Khan and all staff members of PIDE, who helped me whenever needed.

I have limitations of words to thank Dr. Ghulam Mustafa for his kind assistance and help during research. I thank my senior friends and fellow students at PIDE, Dr. Saud Ahmed, Muhammad Sajid Bashir and Hafiz Sajid Imran for their encouragement, thought provoking discussions, help and support.

I also want to express my appreciation to my family (especially Atta Muhammad and Muhammad Ijaz and Arshad Aslam) for their love, understanding, patience, endless financial support, and never-failing faith in me. Finally, I am indebted to my wife Asia Mujahid, my lovely sons Muhammad Azan and Shahzain Malik and my doll Dua Fatima for their love, which remained an inspiration throughout.

ABSTRACT

The underlying dissertation aims to conduct three research essays on covariate shocks and social protection. The first essay explores the relationship between occurrence of covariate shocks at tehsil level and households' well-being by using HIES (2018-19). The well-being is measured by indicators, such as log of per-adult equivalent, log of monthly income, log of calorie intakes, and log of food and non-food expenditure share to the total expenditures, whereas covariate shocks are measured by rainfall and temperature, and flood shocks. By and large, the estimated results demonstrate that covariate shocks reveal adverse impacts on the household's well-being outcomes. Likewise, the application of binary Logit Model also suggests that flood and climatic shocks have adverse impacts on determining the poverty and food insecurity status of the households. We have applied Generalized Ordered Logit (GOL) model on five ordered quantiles of the expenditures, monthly income, and calories intake by households to quantify the variations in the magnitude of the co-efficient. The results establish that covariate shocks are more hurting the lower quantiles, as compared to the higher quantiles of the expenditures, income, and calorie intakes. These findings establish two implications: i) on the whole, all households are exposed to the climatic shocks, while the magnitudes of influences vary with respect to resilience capacity of the households, and ii) especially, households belonging to poorest quintiles are more exposed to the covariate shocks than the richer income quintiles. So, effective and inclusive social safety nets, which are directly designed for cushioning against the covariate shocks are required to be implemented. For that purpose, the mechanism of the BISP needs to expand for those who are extremely vulnerable to the flood and climatic shocks.

The second research essay evaluates the mediating role of social protection expenditures on achieving well-being agenda against the economic and climatic shocks in developing countries at macro-level. The study has employed three indicators of well-being i.e., food insecurity, national level household expenditures, and accumulation of human asset. For empirical purpose, we use the unbalanced panel data of 94 developing countries. The selection of the countries is based on the availability of data (2001-2019) on economic and environmental vulnerability. For empirical purpose, the underlying study has applied the country fixed effect model.

The estimated results suggest that the social protection expenditures have the significant mediating role against the economic and environmental shocks in order to maintain the national level food security, increase in household expenditures as well as escalation in human asset accumulation in developing countries. The study also highlights that social protection expenditures have much stronger mediating role against environmental shocks as compared to macro-economic vulnerabilities. The results of this essay suggest a strong policy implication, and these can motivate the policymakers as well as the governments of the developing countries to increase the expenditures on social protection programs. Primarily, these findings substantiate the significance of the first essay. The moderating role of the cash transfer programs are expected to be increasing as the governments enhance their budgetary allocation on implementation of the social protection programs.

After establishing the adverse impacts of covariate shocks on households' well-being, and the mediating role of social protection programs against economic and environmental vulnerabilities, it comes out that there is a certain need to design a shock adjusted policy framework. As Pakistan being the highly vulnerable country to the economic and environmental shocks, the role of BISP cash transfer becomes highly important. The current targeting method of BISP is highly depending on the formulation of PMT score, it is static in nature, as it is not capturing the impacts of covariate shocks. So, third essay primarily focuses on the shock adjusted targeting method for BISP. This analysis is chiefly based on Household Integrated Expenditure Survey (HIES) 2018-19 conducted by Pakistan Bureau of Statistics. The sample consists of 24,809 households from four provinces (Punjab, KPK, Sindh, and Balochistan). From HIES, we have estimated the PMT score without shocks, while other socioeconomic profile of households is also measured from said household survey. The data of tehsil level flood water covering area (square kilometer) is collected from NASA MODIS Satellite data. While, the tehsil level climatic data of rainfall and temperature is taken from European Center for Medium-Range Weather Forecasts (ECMWF). In order to merge it with tehsil's information, we acquired the code classification of tehsils of HIES 2018-19 from PBS. After identification of tehsils from HIES household survey data, we merged all flood and climatic variables by using tehsil codes as their key identifiers. After this, we estimated shock adjusted PMT score after merging covariate shocks data with HIES data. Overall targeting performance of shock adjusted model increased to 67 percent as compared to 60 percent targeting performance of without shock model. Coverage of bottom 20 percent from urban areas decreased to 42 percent as compared to 55 percent previously. Urban areas were given over coverage in previous model adopted by BISP based on HIES 2013-14. This motivated us to suggest policymakers to adopt shock adjusted targeting method because it is not only dynamic in nature but it also captures dynamic nature of poverty in Pakistan.

By summing up the above-mentioned three research essays, the findings establish policy implications as follows: Government should design social safety nets according to the climatic and environmental shocks. As BISP is one of the largest social protection programs, it must be extended to the flood-prone disasters, and climatic-shocks. Specifically, policymakers must prioritize the lower quantile to enable them to cushion the adverse impacts of the climatic and flood-prone disasters. Flood disaster appears to be the highly disastrous calamity, government must link the social safety nets with National Disaster Management Authority (NDMA), so that vulnerable households may target earlier, and rescue them from being food insecure and from chronic poverty. BISP administration should revisit the formula of PMT score to target the people. The new PMT should be shock adjusted, such as climatic and flood-prone hazards. The adjusted formula may be helpful to identify the highly exposed households.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADB	Asian Development Bank
BISP	Benazir Income Support Programme
CAA	Civil Aviation Authority
CBN	Cost of Basic Needs
CCT’s	Conditional Cash Transfers
CNIC	Computerized National Identity Card
CT’s	Cash Transfers
ECMWF	European Centre for Medium Range Weather Forecast
EOBI	Employees’ Old-Age Benefits Institution
FEI	Food Energy Intake
FFC	Federal Flood Commission
GDP	Gross Domestic Product
GOL	Generalized Ordered Logit
GoP	Government of Pakistan
GSPF	Government Servants Pension Fund
HIES	Household Integrated Expenditure Survey
ILO	International Labour Organization
IPCC	Intergovernmental Panel on Climate Change
KPK	Khyber Pakhtunkhwa
MDER	Minimum Dietary Energy Requirement

MOCC	Ministry of Climate Change
NCCP	National Climate Change Policy
NDMA	National Disaster Management Authority
NDMC	National Disaster Management Commission
NFFD	National Flood Forecast Division
NSER	National Socio-Economic Registry
NSPS	National Social Protection Strategy
OLS	Ordinary Least Squares
PMD	Pakistan Meteorological Department
PMT	Proxy Means Test
PoU	Prevalence of Undernourishment
PSLM	Pakistan Social and Living Measurement
PTA	Pakistan Telecommunication Authority
QPM	Quantitative Precipitation Measurement
SDGs	Sustainable Development Goals
UCTs	Unconditional Cash Transfers
UNDP	United Nations Development Programme
WCES	Workers Children Education Fund Scheme
WWF	Workers Welfare Fund

CHAPTER 1
INTRODUCTION

1.1 Background

All form of poverty reduction is one of the key sustainable development goals (SDGs). In this era of globalized world, life is fraught with multifaceted mix of opportunities and risks, financial crisis, fuel and food created disturbances to world economy as a whole., climate-related and natural disaster-prone shocks are intimidating the vulnerable segments of the developing countries.

Most of the developing countries have limited institutional and financial resources to resist against climatic and environmental shocks. According to Global Climate Risk Index (2020), majority of the countries lying in the list of top 10 most vulnerable countries to climate and environmental shocks belong to the developing countries, such as Dominica, Nepal, Thailand, Bangladesh, Vietnam, Pakistan, Philippines, Haiti, Myanmar, and Puerto Rico. Such countries belong to low and middle-income classification. From 1999 to 2018, around 49,5000 people died worldwide and USD 3.54 trillion were lost due to natural disaster, and more than 12,000 extreme events of shocks and disasters have occurred in the whole world. These threats are projected to be rising over the time, if world does not respond to it wisely and effectively. Likewise, macroeconomic shocks, like inflationary shocks, productivity losses, and recession in developing economies also have significant influence on the lives of the households in developing countries.

The nexus between covariate shocks and households' well-being is well documented by available literature. The adverse shocks impact the resilience power of the poor households, and due to financial constraints, they are highly vulnerable to these covariate shocks. So, these shocks push the ultra-poor households into the chronic poverty which further makes them highly exposed to the covariate shocks (Saeed and Hayat 2020); (Azeem, Mugera et al. 2019); (Kurosaki and Khan 2012).

In the face of such economic and environmental risks and vulnerabilities, the role of fiscal space to provide social protection against the climatic and economic shocks gained significance. Particularly, after the global recession in 2008, international community reaffirmed the provision of social protection to maintain human security due to the vulnerability of the poorest segment of the countries. Therefore, world development agencies, policymakers and governments struggle to identify poor and vulnerable sections of the society to target them. So, in the face of looming threats, the demand of implementation of social protection gained inevitable significance (World Bank, 2018). Social protection is defined as the set of policies and programs which are designed to cope with poverty and food insecurity, and promote the diminishing exposure to risk, efficiency of Labour market.

The global literature indicates that social assistance (CCTs & UCTs) has positive and significant impacts on the socioeconomic betterment of the vulnerable and ultra-poor segments of the society. Moreover, such programmes have increased the socioeconomic well-being of the people, such as poverty reduction, adaptive capacity, food security, and Labour participation (Handa, Seidenfeld et al. 2020); (Ferraro and Simorangkir 2020); (Ambler and De Brauw 2019); (Bhalla, Handa et al. 2018).

These beneficial impacts have motivated the developing countries to start increasing the budgetary expenditures for social protection programmes. Overall, highly vulnerable countries launched social protection programmes, like cash transfer programs and other form of subsidies to the poorest people in order to cushion the adverse effects of the economic and climatic shocks (Ferraro and Simorangkir 2020). Similarly, (Asfaw, Carraro et al. 2017) have suggested the mediating role of social protection Programme against the climatic shocks in Zambia. Social protection programmes are the important instruments which enhance the adaptive capacity of the poor people against covariate shocks through provision of additional income in the form of cash transfers, health insurance, and provision of assistance in other forms. Such provision of social protection increases the resilience power of the communities, and enables them to resist against the climatic and economic shocks (Mustafa, Ali et al. 2019).

In spite of the beneficial impacts of cash transfer programmes, the modality of the targeting has deemed the prominent instrument to reap the effective and efficient outcomes of the programmes. Different targeting methods are used in world to identify poor and vulnerable groups of the society. Common targeting methods are community-based targeting, geographic targeting, self-targeting, mean tests and proxy mean test. In community-based groups, community leaders and members determine household eligibility but this method is vulnerable to elite capture and eligibility decisions can lack transparency (Hulme and Shepherd 2003); (Dercon and Krishnan 2000).

In geographic targeting, targets are set by location, including all residents within a location. It is easy to implement and is transparent, it can rapidly target in response to natural disasters and other large covariate shocks. But it does not account for differences in households' well-being in the area. In self-targeting benefits and transaction, costs are set, so that only needy households enroll. Stigma and lack of Programme knowledge may discourage participation. In mean tests actual consumption or income is compared to eligibility threshold. Mean tests are very accurate with good income or consumption data. But it is expensive to collect income or consumption data for all potential beneficiaries. In Proxy means test consumption is proxies, though it is readily observable and verifiable variables and is compared to eligibility threshold. Internationally proxy means tests are used in different social safety nets as a tool to target the poor households (Devereux, Masset et al. 2017); (Iqbal and Nawaz 2017).

The aforementioned discussion has highlighted the adverse influences of the adverse impacts of climatic and environmental shocks on households' well-being in developing countries. The covariate shocks like flooding, climatic shocks and other covariate shocks can impact the targeting methods e.g., poverty score approach, if only socioeconomic poverty predictors are considered. Growing body of literature has suggested that flooding, heavy patterns of rainfall, and droughts are affecting the prevalence of poverty and food insecurity in developing countries. It suggests, if these covariate shocks are considered as the poverty predictors in estimating the poverty score to identify the eligible for cash transfer programs, it will directly impact the exclusion and inclusion errors of the targeting method. Moreover, such indicators can influence the effectiveness of the targeting methods and modalities as well.

1.2 Motivation of the Study: The Case of Pakistan

Pakistan is located in the region of South Asia, whose 3 out of 8 members are holding top 10 position in ranking among those countries which are most vulnerable to climate change due to extreme volatility in weather patterns. The more alarming thing is that the weather shocks in Pakistan are expected to continue which would make her highly exposed to the disastrous impacts owing to her poor adaptive capacity against climatic-variability (Eckstein *et al*., 2019). Her climate is diverse, it is tropical and sub-tropical, some areas are coastal, arid and some are semi-arid. The Northern part of the country is high rain fall zone which is covered by mountains with heavy snowfall. Climatic variables such as rainfall and temperature demonstrate huge variability. Moreover, four seasons of rainfall are estimated in Pakistan: pre-monsoon (April-June), monsoon (July-September), post-monsoon (October-December), and winter (January-March) season of rainfall (Faisal and Sadiq; Adnan *et al.*, 2017). The monsoon season comprises irregular patterns of occurrence. Some years get extremely heavier rain seasons which cause flooding; however, some years indicate low patterns. Similarly, pre-monsoon also suggests irregular but drastically high rainfall patterns with stormy winds which disastrously affect people. However, during last couple of decades, average rainfall increased in some parts of the country with extreme rainfall events. In spring (March-April), country experiences thunderstorm and strong wind blowing (Faisal and Sadiq, 2009). In spite of contributing less than 1 percent in annual global emissions, Pakistan is facing increase in average temperature. It is projected that average temperature of the country would rise by 3-4^{o} C during next couple of decades, and it would raise 5-6^{o} C by the end of this century. The observed warmest months are May-July with extreme events of maximum temperature. Nonetheless, on average December-February are the coolest months (Ahmed *et al.*, 2016). The frequency of the hottest days is going to be scaled up and winter duration is shortened with extreme events of minimum temperature. Both summers and winters are showing great intensity in weather periods which makes her highly vulnerable country. These intense weather cycles result in rising sea levels, abnormality in precipitation patterns, catastrophic waves of flooding, and depletion of environmental resources (Eckstein *et al*., 2019).

The adverse shocks impact the resilience power of the poor households, and due to financial constraints, they are highly exposed to the occurring shocks. So, these shocks push the ultra-poor households into the chronic poverty which makes them highly exposed to the covariate shocks further. Further evidence on impacts of climatic shocks on well-being in Pakistan has shown that adverse shocks leave negative impacts on households' livelihood and earnings in Pakistan. Likewise, the occurrence of natural hazards has detrimental impacts on the infrastructure of the country, which further causes poverty and food insecurity in Pakistan. In the face of above-mentioned threats, the role of social protection Programme has gained importance to assist the ultra-poor households against the shocks. Specifically, the role of Benazir Income Support Programme (BISP) is highly important due to its modality, and infrastructure.

The BISP is one of the largest social protection programs in South Asia due to its administrative infrastructure and coverage (Watson, Lone et al. 2017). The incumbent federal government of Pakistan launched BISP to cushion the adverse impacts of food inflation in 2008. The BISP was designed to maintain consumption smoothing of the ultra-poor households. Moreover, the broader objective of Programme was to fulfill the redistributive goals of the country by disbursing the minimum level of cash transfer to the ultra-poor households, which is extended to over 5 million beneficiaries of the program (GoP, 2016).

In beginning, beneficiaries were selected through parliamentarians, because of unavailability of data and proper criterion about eligible people which raised doubts on the transparency and effectiveness of BISP. In the second phase, "Poverty Scorecard" survey, which is known as National Socioeconomic Registry (NSER), was conducted in 2009-10, which enabled BISP administration to calculate poverty scorecard using Proxy Mean Testing (PMT) on the basis of 23 socioeconomic predictors of poverty. In order to identify the eligibility for BISP, a threshold of 16.17 is specified, below this cut-off, those households are considered eligible that have married women some[1]. These ever-married women must hold Computerized National Identity Card (CNIC), and they must get themselves registered in local offices of BISP to be considered as the beneficiaries of the Programme. Initially, eligible households enrolled under BISP were given Rs. 3,000 per quarterly. However, the benefit level gets increased steadily. With increasing value of dollar, benefit amount was also increased up to around Rs. 5,000 quarterly.

Primarily, the BISP targeting was relying on socioeconomic poverty predictors, which ultimately formulated the poverty scorecard to identify the potential beneficiaries. Due to the static nature of targeting method of BISP Programme, the administration may incur potential exclusion error by excluding prospective beneficiaries who become poor due to climatic shocks. Moreover, BISP poverty scorecard is sensitive to the dynamic nature of poverty, which is more sensitive amid the looming detrimental impacts of flood-prone shocks, climatic shocks, and inflationary shocks which are outcomes of macroeconomic instability. These factors can affect the effectiveness of the eligibility criterion of the Programme. As literature has shown the adverse impacts of climatic and environmental shocks on poverty and food insecurity, these poverty predictors can influence the PMT score, which ultimately may impact the inclusion and exclusion errors of the programmes. These covariate factors are the instruments of chronic poverty; therefore, the inclusion of these indicators will improve the effectiveness of eligibility criterion of BISP cash transfer Programme. Hence,

[1] These exceptions include households could receive cash transfer which have PMT score between 16.17 and 21.17 conditional on: 1) family containing at least one disable member, 2) presence of at least one senior citizen, and fewer than three members, and 3) households which have four or more children below 12 years.

aforementioned indicators may generate the covariate shock-adjusted PMT score to identify the eligible households for BISP.

Covariate shocks negatively impact household well-being which is proved by different studies. There is a need to investigate how covariate shocks effect different groups (quantiles) of household. It is proposed that covariate shocks differently impact different groups of households. Negative impacts of these shocks are high on the household which are in lower group (quantile), as their resilience power is very low, as compared to household in the higher groups (quantiles).

It is also proposed to increase fiscal space to cater the negative impact of covariate shocks at the macro-level to provide social protection to vulnerable household's modality of targeting is very important. Thus, there is a need to revisit the current targeting method followed by the BISP, which is static in nature and doesn't capture the impacts of shocks.

This motivates us to establish the negative impact of covariate shocks on household well-being. We also want to establish the mediating role of social safety nets. Once negative impact of covariate shocks is established, it becomes important to incorporate covariate shocks in targeting methodology.

1.3 Objectives of the Study

Primarily, the ongoing dissertation maintains focus on the modality of the BISP cash transfer programs. For this purpose, three essays are established to estimate the generation of the shock-adjusted poverty scorecard, impacts of covariate shocks on households' wellbeing, and estimate the mediating role of fiscal allocation on social protection programmes from global perspective. Hence, the specified essays are given as follows:

1.3.1 Specified Objective of Essay-1

This essay maintains focus on exploring the impacts of climatic and flood-prone shocks on households' well-being by using HIES 2018-19. Tehsil level covariate shocks are incorporated to investigate their impacts on households' well-being. Following are the specified objectives:

1. To evaluate the impacts of climatic shocks (rainfall, temperature shocks and flood shock) on households' well-being indicators — per-adult monthly expenditures, calorie intakes, monthly income and share of food and non-food expenditures with total expenditures.
2. To estimate the impacts of covariate shocks on status of household poverty and food insecurity.
3. To explore the inequality in the impacts of covariate shocks across the quintiles of household expenditures, monthly income, and food security.

   The above specified objectives will provide the justification and guideline to construct the shock-adjusted PMT score to identify the eligible households in third essay.

1.3.2 Specified Objective of Essay-2

The underlying essay aims to evaluate the mediating role of government expenditures on social protection against economic and environmental shocks in developing countries. Actually, the study endeavors to collect the fresh evidence from developing countries regarding their preferences or priorities to expand fiscal space for social protection programmes. The specified objectives of the third essay are outlined as follows:

1. To explore the mediating role of the fiscal/budgetary allocation for social protection against the economic and environmental shocks on food insecurity.
2. To explore the mediating role of the fiscal/budgetary allocation for social protection against the economic and environmental shocks on human asset index.
3. To explore the mediating role of the fiscal/budgetary allocation for social protection against the economic and environmental shocks on national level household expenditures.

1.3.3 Specified Objective of Essay-3

Due to occurrence of covariate shocks and literature, showed its negative impacts on poverty, which enhances the possibility that households which were not eligible for BISP, may become eligible over the time due to economic and climatic shocks. Similarly, there is a possibility that a household that entered in BISP at a certain level of welfare may not need assistance following a significant positive shock. Targeting method followed by BISP is static in nature and does not capture the dynamics of poverty due to shocks. Hence, following is the specified objective of this essay:

1. To calculate a shock-adjusted PMT score which captures the dynamic nature of poverty in Pakistan.
2. To calculate the exclusion and inclusion errors from shock-adjusted PMT score.
3. To suggest the policy recommendation on the basis of obtained findings.

1.4 Significance of the Study

Three essays on ongoing study contribute in multiple ways. Firstly, the first essay estimates the impacts of climatic shocks and flood shocks on different indicators of the well-being. Most of the previous literature regarding Pakistan has estimated the impacts of climatic shocks on food security and poverty, but those studies have some limitations. We have not only established the impacts of covariate shocks on household wellbeing but also decomposed the impacts of shocks on households in different quantiles. This is unique addition to existing literature in form of this essay.

Similarly, second essay also contributes to literatures in which we have estimated the mediating role of budgetary allocation on social protection programmes against the economic and climatic shocks. In literature there are few studies which have established the mediating role of social protection against economic and environmental vulnerabilities at micro-level but no such study is found at macro-level. Thus, ongoing essay has found evidence from macro-level and includes very comprehensive indicators of macro-level well-being indicators from developing countries. In this essay, we established the mediating role of social protection expenditures against economic and environmental vulnerabilities at macro-level.

The third essay is supposed to be the main contribution to the study, which computes the shock-adjusted PMT score from HIES 2018-19 to specify the BISP cash transfer potential beneficiaries from HIES/PSLM. The previous PMT score for BISP is computed from the NSER during 2010-11, which mainly depends on socioeconomic predictors of the poverty, and it missed the expected occurrence of climatic and flood-prone shocks. These shocks are the instruments of the chronic poverty, especially for highly exposed households (Iqbal and Nawaz 2017) have estimated the inclusion and exclusion errors of the BISP modality. Hence, the ongoing essay has constructed the shock-adjusted poverty scorecard which is expected to be very effective policy instrument to re-estimate the targeting performance and targeting efficiency (exclusion and inclusion errors) and it could help to identify the new potential eligible households which are highly exposed to climatic and flood-prone shocks. Thus, this dissertation gives three policy-oriented essays to literature, which will not only help policymakers, but will also open new dimensions of research in this area.

By summing up the above-mentioned three research essays, the findings establish policy implications as follows: Government should design social safety nets according to the climatic and environmental shocks. As BISP is one of the largest social protection programmes, it must be extended to the flood-prone disasters, and climatic-shocks. Specifically, policymakers must prioritize the lower quantile to enable them to cushion the adverse impacts of the climatic and flood-prone disasters. Flood disaster appears to be the highly disastrous calamity; government must link the social safety nets with national disaster management authorities (NDMA), so that vulnerable households may be targeted earlier, and rescued from being food insecure and chronic poverty. BISP administration should revisit the formula of PMT score to target the people. The new PMT should be shock adjusted, such as climatic and flood-prone hazards. The adjusted formula may be helpful to identify the highly exposed households.

1.5 Organization of the Thesis

Rest of the dissertation is organized as:

Chapter 2 deals with Social Protection and Climatic Shocks: A review of existing polices and stakeholder's feedback/ Interviews. Chapter 3 deals with the 1st essay of the dissertation titled: Covariate Shocks and Household Well-being in Pakistan. Chapter 4 deals with the 2nd essays of the dissertation titled: Mediating the Impact of Economic and Environmental Vulnerabilities on the Well-being in the Developing Countries. Chapter 5 deals with the 3rd essay of the dissertation titled: Targeting Performance: Proposal for Shock Adjusted Targeting Method.

CHAPTER 2

SOCIAL PROTECTION AND CLIMATIC SHOCKS: A REVIEW OF EXISTING POLICIES AND STAKEHOLDERS' FEEDBACK INTERVIEWS

The main concern of this chapter is to weave up the overview of existing social protection and climatic change policies at national level. This chapter also discusses policy feedback of stakeholders in relevant sections. Chapter is organized as: Section 2.1, which discusses about national social protection strategy of Pakistan. Section 2.2 deals with the budgetary allocations for social protection programmes. Section 2.3 comprises the overview of the climate forecast and disaster management agencies in Pakistan. Section 2.4 deals with introduction of Ministry of Climate Change, Government of Pakistan. Section 2.5 and 2.6 deals with the feedback interviews of policymakers and academia stakeholders.

2.1 National Social Protection Strategy of Pakistan

Pakistan's constitution specifies social protection as an unambiguous fundamental right in Article 38(a) (d) and (e), (GoP 1973) as under:

"The State shall provide for all persons employed in the service of Pakistan or otherwise, social security by compulsory social insurance or other means; provide basic necessities of life such as food, clothing, housing, education and medical relief, for all such citizens, irrespective of sex, creed, caste, or race, as are permanently or temporarily unable to earn their livelihood on account of infirmity, sickness or unemployment; reduce disparity in the income and earnings of individuals."

Historically, social protection was taken as an interim or an ad-hoc intervention to circumstances rather than a part of social protection policy, or it was advocated by the international donor agencies Assurances made in the Article 38 of the constitution of Pakistan (GoP 1973) remained unfulfilled for its citizens. It could be because of two reasons (a) huge finances are required, which is an acute problem in developing countries and Pakistan has no exception, and (b) constitutional violations by the dictators.

Planning Commission of Pakistan developed "National Social Protection Strategy" (NSPS) which was approved by the Federal Government in June 2007. NSPS defines social protection as…. *"a set of policies and program interventions that address poverty and vulnerability by contributing to raising the incomes of poor households, controlling the variance of income of all households, and ensuring equitable access to basic services. Social safety nets, social insurance (including pensions), community programs (social funds), and labor market interventions form part of social protection"*

In the same year, NSPS was adopted by the government with the following objectives:

- To support chronically poor households
- To provide protection against inauspicious shocks
- To embolden investment in human and physical capital

The constitution (GoP, 1973) assures the basic fundamental right of social protection for its citizens. Currently, there are several social assistances as well as various social security initiatives have been adopted, which fulfill the commitments made in the above-mentioned constitutional provision. A brief overview of these programmes is in following subsections:

2.1.1 Brief Overview of Social Protection Programmes in Pakistan: Prior 2008

Social protection system indicates the design and implementation of the social and economic policies in order to reduce poverty and vulnerability in certain outcomes by extending relief to the highly marginalized segments of the community. Such programmes aim at invigorating the capacity of the highly vulnerable and exposed individuals to cope with economic and natural hazards (GoP, 2019-20). In Pakistan, a number of programmes have been launched to target the poor households—Bait-ul-Mal, Zakat and Usher programs, Workers Welfare Fund (WWF), Employees' Old-Age Benefits Institution (EOBI), and Provincial Employees' Social Security Institutions. These are working prior to 2008. However, after 2008, BISP becomes the largest social safety net in Pakistan (GoP, 2019-20).

Prior to BISP, two types of programmes were working: i) social security, and ii) social assistance. Social security or social insurance was designed to assist the Labour, working in formal sectors (both public and private sectors). The primary benefits include pensions, sickness allowances, old age benefits, and social insurance. A brief description of both social security/social assistances related programmes is given in table 2.1. In 1954**,** *Government Servants' Pension Fund (GSPF)* was initiated, which provides benefits to all government employees after retirement. In 1967, *Employees' Social Security Institutions* was established for private workers, especially those who were working in industrial sectors. After that *Workers Welfare Funds* (WWF) in 1971, *Workers' Children Education Scheme* (WCES) in 1972, and *Employees' Old-age Benefits Institutions (EOBI)* in 1979 were started to provide multiple benefits to the workers (ADB, 2004; Jamal, 2010). Social assistance programmes are designed to extend the support to the highly vulnerable people. For this purpose, multiple social assistance programmes have been launched, and these programs include *People's Rozgar Program, People's Worker Program, Zakat*, *Bait-ul-Mal,* and *Labour Market Programmes* before 2008.

Table- 2.1: Overview of Major Social Protection Programmes in Pakistan

Category	**Benefits**
Social Security Programmes/Social Insurance	
Government Servants' Pension Fund	Provident fund and old-age pension (for government employees)
Employees Social Security Institutions	Health services and cash assistance (for private formal sector)
Benevolent Fund and Group Insurance	Benevolent funds and insurance
Workers' Welfare Fund (WWF)	In-kind-support, cash and housing
Workers' Children Education Ordinance	Free education for workers' children
Employees' Old-Age Benefits Institutions (EOBI)	Old age-pension, cash grant
Social Assistance Programmes	
People's Rozgar Programme	Provision of loan with subsidized interest rate
People's Worker Programme	Wages (unemployed Labour)
Microfinance	Loans
Zakat	Cash support
Pakistan Bait-ul-Mal	Both cash and in-kind support
Food Support Programme of Bait-ul-Mal	Conditional cash transfer
Benazir Income Support Programme (BISP)	Unconditional cash transfer
Ehsaas Programme	Cash and loan support

Source: Jamal (2010) & GoP (2019-20)

The Zakat and Usher Programme was established in 1980, which is purely working by private contributions. It is considered as one of the significant modes of charity in Islamic system. Another significant social assistance is a *Pakistan Bait-ul-Mal*, which is well-established institution (GoP, 2019-20). Nonetheless, there are some provincial social assistance programmes which include Grant of State Land to Landless Peasants (Sindh), Rural Support Programme for Poverty Reduction, Punjab Vocational Training Authority, Youth Development Programmes, and Chief Minister's Self-employment Scheme. BISP is largest social assistance Programme in terms of budgetary allocation and coverage, as compared to all other social assistance and social security programmes in Pakistan.

2.1.2 Social Assistance Programmes after 2008

After 2008, two major social safety nets were launched by incumbent federal government, i.e., BISP and Ehsaas Programme. BISP was launched in 2008 by incumbent federal government of Pakistan in order to cushion the impacts of the food inflation. Short run objectives of the Programme were to maintain consumption smoothing, while long run objectives were to build adaptive capacity of the poor households, which were highly exposed to covariate shocks. Moreover, the administrative units of BISP are established in each tehsil, while headquarter is in Islamabad, and six sub-headquarters are built at each provincial capital. Such well-established infrastructure and coverage make BISP one of the largest social assistance programmes in Pakistan (GoP, 2018, (Watson, Lone et al. 2017)).

Targeting of the BISP was done in two phases. In first phase (2008-10), the identification of eligible households was performed by parliamentarians, and they selected the most vulnerable households from their own constituencies. This process raised doubts on the effectiveness and transparency of the BISP. In second phase (2010 to onward), the targeting was made through poverty scorecard on the basis of different poverty predictors. The threshold of the poverty score was specified 16.17, households below this score were considered beneficiaries (Ambler and De Brauw 2019). The selected households were provided PKR 5,000 quarterly. The documented reports have indicated the significant impacts of BISP cash transfer on household's wellbeing. In 2016, The Oxford Policy Management did the impact evaluation of BISP, and followings are the most salient features of its findings:

- BISP supports the poor households to increase their food consumption and to empower women.

- Complimentary programmes such as Waseela-e-Taleem increases the child school enrollment.
- Almost 96% beneficiaries have shown satisfaction over the mechanism of cash transfer.
- The reports revealed that around 95% of the beneficiaries are highly vulnerable.

Apart from these reports, the researchers also attempted to estimate the impacts of BISP cash transfers on women empowerment, political behavior, and food outcomes. Their findings reflected the significant and positive impacts of BISP (Jalal, 2017) (Ambler and De Brauw 2019). The Ehsaas Programme has been launched by the incumbent government in 2019. It consists of many programmes, such as Youth Skill Development Programme, Ehsaas Kafalat Programme, and Emergency Cash Transfers. The crux is that, these programmes are the extensions of the BISP (GoP, 2019-20).
relevant chapter.

2.2 Budgetary Allocation on Social Protection in Pakistan

The government of Pakistan has shown relatively much interest in spending on social protection programmes despite limited fiscal space. Expenditures on social security and welfare are having the increasing trend. Especially, after 2008, the expenditures on social security and welfare are showing fast increase in government expenditures (figure-2.1).

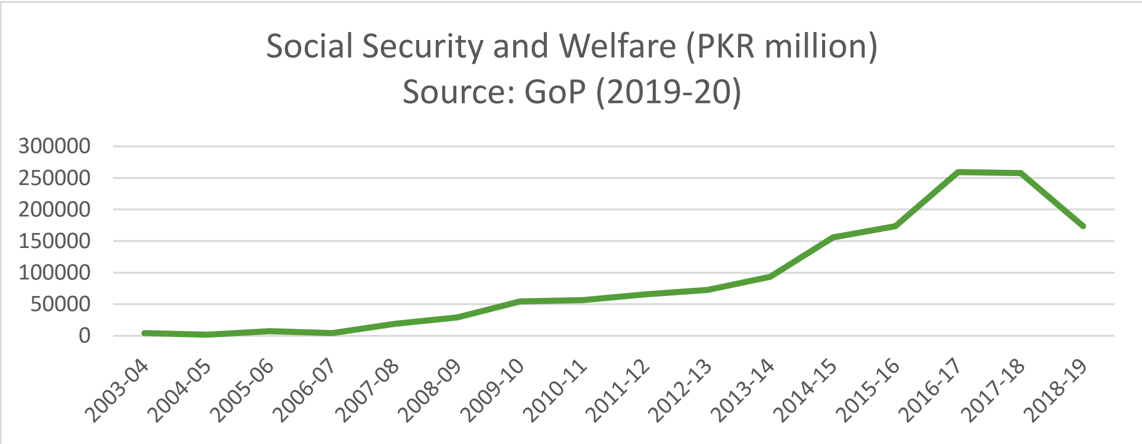


Figure-2.1: Government Expenditures on Social Security and Welfare

Moreover, the government of Pakistan has released PKR 762.73 billion on BISP Programme from 2008 to 2019. This total released amount for BISP has been disbursed to eligible household in the form of unconditional cash transfers (UCTs) of PKR 665.76 billion and conditional cash transfer (CCTs) of PKR 25.7 billion. The budgetary allocation is showing the increasing trend in the expenditures on BISP cash transfer (Table-2.2).

Table-2.2: Government Spending on BISP (PKR billion)

Years	**Released Fund**	**UCT**	**CCT**	**Total=UCT+CCT**
2008-09	15.32	15.81	0.04	15.85
2009-10	39.94	31.94	2.89	34.83
2010-11	34.42	29.66	5.30	34.96
2011-12	49.53	41.60	4.28	45.88
2012-13	50.10	43.30	3.17	46.47
2013-14	69.62	65.11	1.20	66.31
2014-15	91.78	88.59	0.45	89.04
2015-16	102.00	96.65	1.88	98.53
2016-17	111.50	102.10	2.27	104.37
2017-18	107.00	99.00	3.20	102.2
2018-19	91.52	52.00	1.02	53.02
Till Apr, 2019	762.73	665.76	25.7	691.46

Source: Pakistan Economic Survey (2018-19)

In addition to this, Figure 2.2 also depicts the expenditures on other poverty related indicators, which work to reduce poverty. It is evident from the Figure 2.2 that the government has increased the budgetary allocation for road infrastructure. But the government has spent a relatively meager amount on the projects related to water and sanitation, natural hazards, and rural development programmes.

Source: GoP (2019-20)

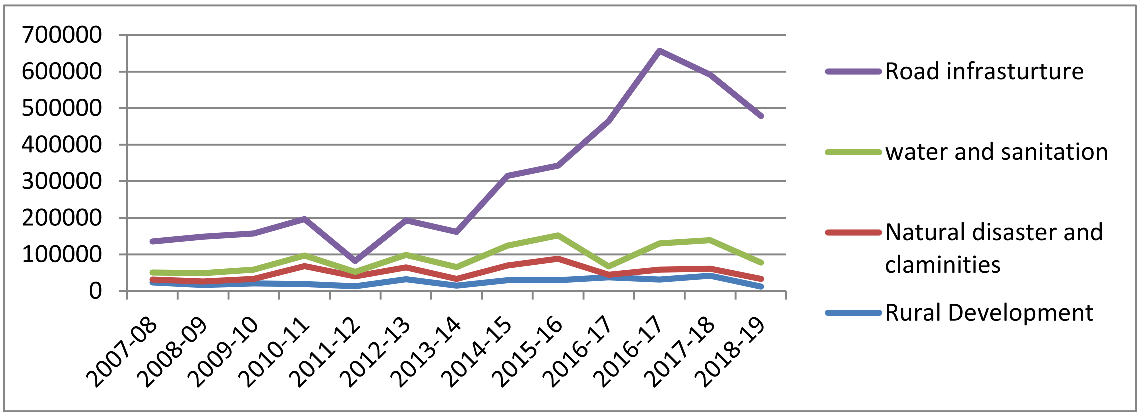


Figure-2.2: Government Spending on Pro-Poor Schemes

Furthermore, the government also took other initiatives to improve the living standards of the retired employees. For this purpose, it increased the budgetary allocation on EOBI initiatives like old-age grant, survivors' pension, and old-age pension, whereas, invalidity pension has been decreasing since the last 6 years (Figure-2.3).

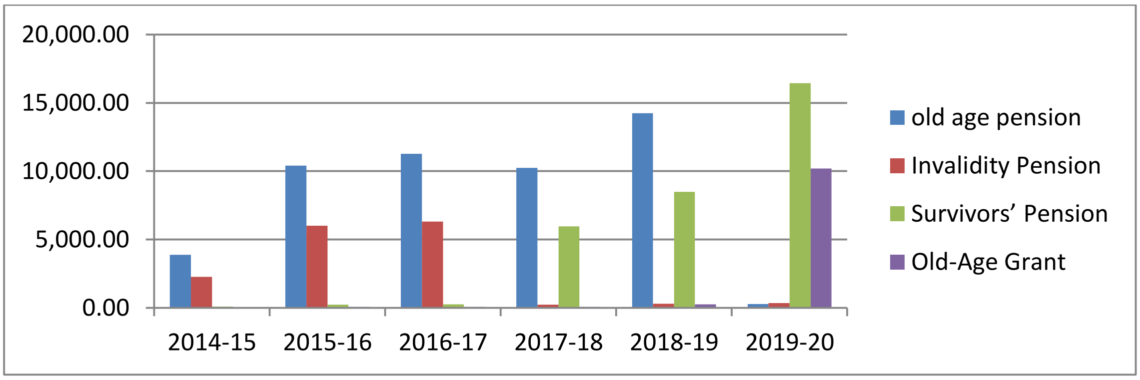


Figure-2.3: Budgetary Allocation on EOBI (Source: GoP 2019-20)

World Bank (2018)[2] reported that developing countries spend only 1.5% of their GDP on social assistance programmes, while European and Central Asian countries spend 2.2% of their GDP on social safety nets. In addition to this, the report also reveals that Sub-Saharan and Latin American countries are spending 1.5% of their GDP, whereas, South Asian countries spend around 0.9% of their GDP on social protection programmes. It makes clearly evident that the South Asian countries are relatively spending low on social protection programmes as compared to the rest of the world.

The comparison of South Asian countries in terms of spending share to GDP on social assistance is shown in the Figure 2.4. The regional average of public spending on social assistance is about 0.9% of GDP, and it is less than 1% as compared to 2.2 percent of GDP in developed countries. However, India, Nepal, and Maldives are spending more than 1% of their GDP. If we closely look at Figure 1.4, Pakistan is at the second position from bottom to top and it is spending only 0.58 percent of GDP on social assistance.

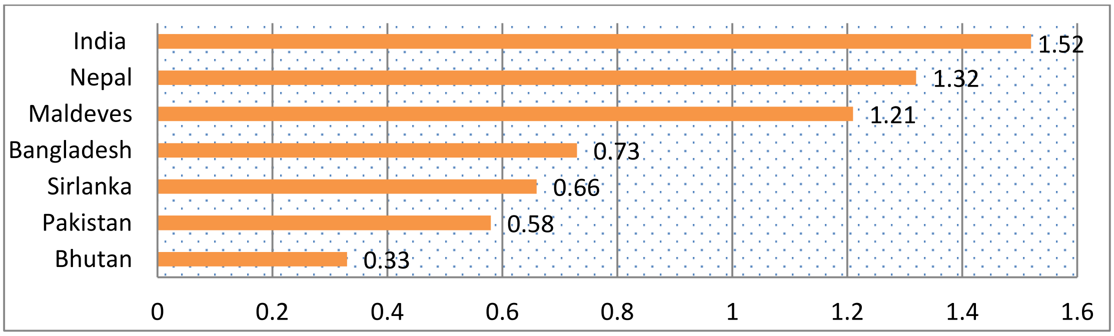


Figure-2.4: Annual Spending on Social Protection in South Asian countries (% to GDP) Source: World Bank

[2] See http://documents.worldbank.org/curated/en/427871521040513398/pdf/124300-PUB-PUBLIC.pdf

The above discussion reveals that Pakistan has launched many social protection programmes, and it has allocated billions to improve the lives of its poor citizens. Among these social protection programmes, BISP is the largest social safety net of the country. Although, Pakistan has increased its expenditures on social safety nets, but these spendings are much lower, as compared to the other South Asian countries.

2.3 Climatic Forecast and Disaster Management Agencies in Pakistan

Pakistan Metrological Department (PMD) was established in 1947 with multiple objectives such as, to provide information on weather, climatic changes, impact-assessment and mitigation of disaster, agricultural development based on climatic potential of Pakistan, glacier monitoring and research, glacier lakes outburst flood (GLOF) warning, future projection of climate and adaptation practices in different sectors. The major accomplishments of PMD include, the introduction of modern flood prediction system, computerized weather forecasting system, earthquake and nuclear explosion detection system. It has well-equipped radar system and satellite technology that enables this institute to provide consultancy regarding flight safety to Civil Aviation Authority (CAA). It also offers consultancy services in making seismic design of dams, and it also gives advisory to federal and provincial governments regarding disaster relief schemes. Research and relief organizations like Federal Flood Commission (FFC), National Disaster Management Authority (NDMA), climate change division, National Food Security started their working with the initial assistance of PMD. In the beginning, PMD, National Flood Commission (NFC, 1977) and Emergency Relief Cell (ERC) were the major relief agencies which were responsible for disaster management, but later on National Disaster Management

Authority (NDMA, 2007) was established. In 2010, National Disaster Management Act was passed and NMDA was made executive arm of National Disaster Management Commission.

2.3.1 Flood and Rainfall Measurement System in Pakistan

In 1978, Pakistan Meteorological Department established National Flood Forecasting Division (NFFD) with the collaboration of UNDP. The prime responsibilities of NFFD are the collection of meteorological, as well as hydrological data and its analysis. Besides this, it is also responsible to collect flood forecast data to make prior necessary preparation, and it also announces early warnings of flood to prevent severe disaster. The operations of NFFD are backed by WAPDA and Quantitative Precipitation Measurement (QPM) Radars. Measurement of water flow is in the operational control of WAPDA. For this purpose, WAPDA has established RIM stations at different catchment areas of Indus River. RIM station at Kachura measures snow melting and inflow of water. Seven weather surveillance radars are installed at Islamabad, Karachi, Dera Ismail Khan (DI Khan), Sialkot, Mangla and Lahore. In addition to this, precipitation measurement radars are also installed at Lahore, Sialkot and Mangla. NFFD receives data from all stations, and this received data is analyzed to forecast flood after every six hours, and this flood forecast is issued to concerned agencies.

2.4 Ministry of Climate Change, Government of Pakistan

In 2012, the Government of Pakistan established world's first full time Ministry of Climate Change. In the same year, the Government of Pakistan also approved National Climate Change Policy (NCCP) with the following objectives:

- To achieve sustainable development by addressing climate change challenges

- To integrate national climate change policy with national and international policies
- To curtail risks emerging from severe climate changes and weather condition, like droughts, precipitation and flood shocks
- To promote natural resource conservation and sustainability in the long run
- To increase coordination among ministerial decision-making

2.5 Feedback Interviews from Policymakers

For bettering designing of research, we have done feedback interviews of different relevant policymakers in government ministries. Detailed interviews and their feedback are given in following sections:

2.5.1 Feedback Interview from Director General Cash Transfer BISP (Mr. Noor Rehman)

The BISP is one of the largest social protection programmes in South Asia due to its administrative infrastructure and coverage. In 2008, the federal government of Pakistan launched BISP to cushion the adverse impacts of food inflation. The BISP was designed to maintain consumption smoothing of the ultra-poor households. Moreover, the broader objective of Programme was to fulfill the redistributive goals of the country by disbursing the minimum level of cash transfer to the ultra-poor households, which has been extended to over 5 million beneficiaries of the Programme. Waseela-e-Taleem was launched under the umbrella of BISP with the objective to support primary education through the provision of PKR 1,500 for male and 2,000 for female quarterly, for the children of BISP beneficiary households with the condition that the beneficiary households will send their children to school. In

2012, this program was initially launched in five districts as a pilot project, but in July 2020 it was extended to whole country.

Covid-19 pandemic took millions of lives and it also impacted economies at unprecedented pace and magnitude. Pakistan, being the developing and 5th populous country in the world, has no exception to it. According to government's estimates, Covid-19 roughly impacted 24.89 million workers in Pakistan. Average household size in Pakistan is 6.45, thus Covid-19 impacted 160 million people, which is roughly two-third of country's population. To avert risk of hunger and economic hardship of the poor, GoP, under the umbrella of BISP, launched Ehsaas cash emergency Programme worth PKR 203 billion to reach 16.9 million households. World Bank recognized BISP performance and ranked it fourth globally in terms of coverage and third in terms of targeting. Poverty Alleviation and Social Safety Division also launched Ehsaas Kafalat, Ehsaas Amdan, Ehsaas Interest Free Loans, Ehsaas Langar, Ehsaas Scholarship, Ehsaas Koi Bhoka Na Soye programmes to uplift the poor.

Hybrid targeting method was used for Ehsaas Cash Emergency Programme. For the demand-based support, requests were received through 8171 short SMS code. There are different targeting tools including verified means test, unverified test and Proxy Means Test, geographic and community-based targeting to identify the poor. A large segment of Pakistan's economy is undocumented, thus BISP uses Proxy Means Test to identify the poor. Proxy Means Test ranks household well-being from 0 to 100. Before covid-19 cut off score was 16.17 but during covid-19 cut off score was increased to 38.

The targeting method, however, followed by BISP is static in nature but BISP ranking in terms of targeting performance is much better in the region. On the other hand, the Dynamic Targeting Method is more effective, as it provides us the real time shock adjusted household well-being to identify the shock affected households and it is followed by Chile, Kenya and few other countries. For Dynamic Targeting Method, the availability of real time data is crucial as NSER is updated after 10 years in Pakistan. Moreover, the availability of real time climatic and economic shocks data is also difficult in Pakistan. Young researchers and many think tanks have been working on it and definitely in the long run we have to move towards Dynamic Targeting Method to capture the dynamic and transient nature of poverty.

Underlying dissertation contributes many folds, we have not only estimated covariate shocks impact on household well-being but we have also simulated shock adjusted targeting method. The performance of our proposed shock adjusted targeting method is much better as compared to the targeting method, followed by the BISP, detail is given in the relevant chapter.

2.5.2 Feedback Interview from Member of Social Sector & Devolution, Ministry of Planning, Development, Reforms and Special Initiatives GoP (Dr. Shabnum Sarfraz)

Social protection programmes are definitely the most valuable tool for redistribution of wealth in a society, and to lift up the most deprived. Even in the most industrialized and economically strong countries, there are some people who are left behind. Social protection programmes like EHSAS ensure that no one is left behind in terms of access to resources. Covid-19 has brought with it many shocks to the markets, resulting in the most vulnerable being disproportionally affected by those economic shocks. In such unprecedented circumstances, it was recognized that social protection programmes could play a pivotal role in uplifting the under-privileged segments of society. "*Pakistan's cash transfer program is one of the few globally lauded emergency cash transfer programs which ensured that the kitchens continued to* *operate for the families in the lowest wealth quintiles during the worst economic and health disaster that hit the globe in this century".* Cash transfer programmes involve extremely intricate, well-documented institutional machinery, cohesion and clarity. Cash transfer programmes like Ehsaas also requires transparency and accountability to ensure effective and efficient provision of funds. Moreover, the process for cash transfers must be exempted from bureaucratic red tape. Ehsaas is ensuring that these factors are addressed in both design and implementation. The next stage is devising dynamic monitoring frameworks for impact assessment to see what is working, and scaling that up. "*To uplift the most vulnerable segment of the society during Covid cut off score household is increased on adhoc basis. There is a need to revisit the cut off score through adjusting shock like covid, economic and climatic shocks. Thus, there is a need to reevaluate the targeting mechanism of BISP for efficient disbursement of social protection schemes".*

There can be an amalgamation of all public social protection programmes under one unit, however, one absolute social protection Programme seems undemocratic and prone to autocratic tendencies of public officials. The federal structure of Pakistan allows co-existence of these programmes for province-specific needs and contextualized approaches. Having said that, there is always room for improvement and more synchronized goal setting, which is one of the components that is the focus of Federal Government this year, as per its constitutional mandate.

2.5.3 Feedback Interview from Director, Research and Development-PMD (Dr. Shahzada Adnan)

Vulnerabilities varies from area to area, and these vulnerabilities can be in the shape of floods, heat-waves, and droughts. The capital of Sindh, Karachi, is vulnerable to heat-waves during summer, as well as urban flooding, which probably occurs during monsoon season. Like this, there could be river area flooding in Punjab and KPK, and droughts in some districts of Balochistan. "*Flood area targeting should be technical and community based rather than depending on local Deputy Commissioners. Flood hits a particular area of a district not a whole district. But the old prevailing practices show that the DC of the area declares the whole district as affected. This unscientific calculation of the calamity not only creates financial embezzlements but also leakages".* The most vulnerable district of Pakistan is Tharparkar, located in Sindh, as drought hits it after every three years. It is observed that more than thirty thousand people have to migrate to the eastern bank of the Indus River due to severe natural calamities in the form of flood or drought. This migration not only creates law and order problem but other civic issues as well. Due to floods and precipitations, agricultural productivity is severely affected, so the government should introduce crop insurance scheme to protect the poor farmers. This will definitely improve their resilience power towards natural shocks.

During the different waves of Covid-19, the food security became a big problem for Gulf countries like Qatar, and Saudi Arabia. Thus, it is necessary to protect small farmers from climate related covariate shocks.

"Interestingly these flood or drought shocks affect different households or farmers differently. A farmer with small land holdings is more affected with these shocks, as his coping capacity is less than the loss incurred. But government treat them through same yard stick. For better utilizing of social protection funds, you have to identify income groups of affected areas".

2.5.4 Feedback Interview from Deputy Secretary, Ministry of Climate Change, GoP (Dr. Mazhar Hayat)

During an interview, the Deputy Secretary to the Ministry of Climate Change said that Pakistan is facing intense weather conditions. Moreover, uncertain and unexpected monsoon rains result in floods and droughts. The Hindukush-Karakoram glaciers of Pakistan have been melting due to global warming. On the one hand, Pakistan is facing shortage of dams, but on the other hand, the repeated floods have been the main cause of the siltation of existing dams. He further said that the rising temperature is causing frequent and increased heat waves. These extreme climate changes and weather shocks are also affecting crop patterns and agricultural productivity in Pakistan. He added that Pakistan has made a small contribution to total global greenhouse gases but Pakistan is among the top vulnerable countries to climate change with low financial and technical capacity to adapt to climatic challenges. NCCP is based on two major themes (a) climate change adaptation (b) climate change mitigation. Ministry of Climate Change also identified several sectoral measures under these broad themes for implementation of adaptation and mitigation actions. To cater climate change adaptation, Ministry of Climate Change is taking pre-disaster measures, and it provides responses to the masses through different authorities i.e., NDMA. The Ministry also provides disaster risk mechanisms for short and long run. During the last five years, the Government of Pakistan has planted 2 billion trees across the country. Currently, during Covid-19 pandemic, the government also took an excellent initiative to plant 10 billion trees. This initiative not only provided thousands of jobs to the poor households but it will also help to increase forestation in the long run. With these measures, the government will definitely achieve SDG 13 and 15, which are about climate change actions and sustainable use of terrestrial ecosystems. On the June 5th 2021, World Environment Day, with the theme of ecosystem restoration, was celebrated. This year, Pakistan, with the collaboration of UN, officially hosted the World Environment Day. The United Nations and other 143 participating countries appreciated the efforts and commitment of the current government towards SDG. During budget speech, the Finance Minister announced that government is going to allocate about PKR 14 billion for tree plantation drive. This shows government's sincere commitment to climate change adaptation.

Keeping in view, the national climate change policy of 2012 and the Ministry of Climate Change objectives, dissertation's first and third essay uses the environmental vulnerabilities like flood, precipitation and temperature shocks data to capture the impact of climatic shocks on household well-being. Underlying dissertation not only provides the policy implication for the Ministry of Climate Change, but it also provides a shock adjusted targeting method to target vulnerable segments of the society. The comprehensive details are given in the relevant chapters.

2.6 Stakeholders Feedback Interviews

This section consists of feedback interviews of stakeholders. We interviewed Dr. Safdar Ali Sohail and Dr. Imran Sharif Choudhry. Dr. Safdar Ali Sohail is a distinguished fellow at Social Protection Resource Centre, Islamabad. He is also the Dean at National Institute of Public Policy, Lahore. Dr. Imran Sharif Choudhry is the Dean Faculty of Social Sciences at Bahuddin Zakariya University, Multan. He has supervised a number of Ph.D. dissertations about poverty and has many publications in national and international journals.

2.6.1 Dr. Safdar Ali Sohail (Distinguished Fellow at SPRC Islamabad, Dean NIPP, Lahore)

The notion of social protection has attained momentum since 2000. Although Millennium Development Goals (MDGs) agenda did not give adequate attention to idea of social protection. In 2015, one hundred ninety-three countries of the world showed their full willingness to achieve the universal social protection target of UN through SDGs upto 2030, as they gave explicit attention to social protection. The most important goal of SDG is to "*end poverty in its all forms, and to implement nationally appropriate social protection system and measures for all, including floors, and by 2030 achieve sustainable coverage of the poor and the vulnerable*". Moreover, its goal number 10 also emphasize to ease off poverty as it states *reduce inequality within and among countries.*

In Pakistan, several social security and social assistance programmes have been running but BISP is the largest social assistance Programme. Although BISP is a ray of hope for the poor and vulnerable households but its current model is financially unsustainable in the long run. BISP provides charity based social assistance to the poor, and thus it creates dependency. We should move towards right based social protection approach.

The key points of right based social protection approach are:

- Consider social protection as a right or entitlement, not just as a matter of charity
- Places a vibrant obligation on states to ensure social protection
- Places citizenship, importance of sympathetic social and political circumstances at the center of the justification and provision of social protection
- Focuses on the ability of citizens to claim their social protection entitlements
- Also focuses on the institutional capacity and accountability mechanism to ensure the proper design and delivery of social protection

- Links demand-side with supply-side consideration, as most of the social protection programs appear to be focused on supply side

On the other hand, the government should design contributory social security programmes for formal sectors. The government should take more care of the worst calamity hit areas by introducing social safety nets. The crop insurance should be provided to the affected farmers to mitigate the adverse effects of natural and climatic hazards. We also need to focus on demand-sided social protection in parallel to supply-sided social assistance.

Yes, the targeting method followed by the BISP is static, there is a dire need to move towards a dynamic targeting method. To implement a dynamic targeting method, NSER should be updated annually but in Pakistan, unfortunately, it is updated after a decade".

2.6.2 Dr. Imran Sharif Choudhary (Dean Faculty of Social Sciences, BZU Multan)

After the 18^{th} constitutional amendment and 7^{th} NFC award, a large number of ministries and resources were shifted to provinces. At the moment, the federal government deals with defense, debt servicing, pension and other development projects. Thus, the federal government has low fiscal space for social protection. Provinces should contribute regarding this matter, and they can design social protection policy more efficiently by focusing on their deprived areas. It is evident that Balochistan, rural Sindh and South Punjab are highly poverty concentrated areas of the country. Consequently, the unified policy doesn't fit for the whole country. The decentralized policy should be designed by considering demographical, cultural, geographical, and other factors of the locality.

In my opinion, the government should introduce indirect measures, to help the poor to establish their own small businesses or equip them with technical skills, to uplift the poor. In this way, a large number of employment opportunities will come up as small businesses are more Labour intensive. The direct measures like unconditional cash transfer simply leads to dependency of the beneficiaries upon the state. Unfortunately, BISP is using means or Proxy Means Test to target the poor. The biggest problem with these methods is that they require accurate data to predict reliable results, but the collection of reliable data, in the developing countries like Pakistan, is costly as well as time consuming. BISP should move towards alternative ways as it may involve third party verification for the potential eligible. It can get assistance from NADRA as well as the banks to identify the vulnerable.

Climatic shocks are definitely affecting vulnerable segments of our society. In Pakistan, a large number of farmers have uneconomic land holdings. As a result, they are unable to adopt modern techniques due to financial constraints. Furthermore, the rising temperature and changing patterns of rains are badly affecting our agricultural productivity, and this phenomenon is more obvious in South Punjab region. The South Punjab has been known as a cotton belt region, but the swift climatic changes, especially the excessive rise in temperature has badly affected this belt. As a result of this, the farmers are more inclined towards cultivating corn.

The government tries to help out the farmers by introducing different subsidized schemes on loans, fertilizers, seeds, and most importantly the reduced electricity tariff gives a great relief to the poverty-stricken farmers. But the benefits of these schemes, unfortunately, do not reach to the needy farmers, due to the political influences of the landlords on the government officials. "*I would suggest to classify most vulnerable segment of the society. Segments which are below the poverty line or cutoff score* *they need more assistance. This assistance could be in any form"*. The government can introduce supportive schemes to climate-stricken farmers, these schemes can be initiated in the shape of crop insurance, and support price. Presently, the government is giving support price only for one crop – wheat, and this policy should be extended to other cash crops – cotton, rice, etc. to help the poor farmers. The government should also make more investment in research and development sector to develop high yielding seeds for better agricultural productivity.

It is evident from review of the existing polices and feedback interviews that social protection programmes treat all vulnerable by same yard stick. But covariate shocks hurt severely to households in the lowest quantile. Households in the upper quantiles are least effected. Secondly, targeting method followed by the main social protection Programme (BISP) is static in nature. Current targeting method do not capture the impact of covariate shocks faced by the households.

The current study fulfills these gaps in three essays. In first essay, it is established that covariate shocks impact households' well-being. It is also established that impact of these is higher on households in lower quantiles as compared to households in upper quantiles. Thus, the households in the lower quantiles have lower adaptive capacity, so they need more support. In second essay we have established the mediating role of social protection against economic and environmental vulnerabilities at macro-level. In third essay, a shock adjusted targeting method is constructed, which incorporates the impact of covariate shocks. Current method of targeting followed by BISP is static in nature which does not capture the impacts of shocks.

CHAPTER 3

ESSAY 1: COVARIATE SHOCKS AND HOUSEHOLD WELL-BEING IN PAKISTAN

Abstract

The underlying study has objective to investigate the impacts of the covariate shocks on households' well-being in Pakistan. For empirical purpose HIES (2018-19) data is used, while tehsil level climatic and flood related variables are merged with household dataset. The estimated results suggest that flood shocks have much harmonious influences on households' well-being, such as log of per adult equivalent expenditure, log of monthly income, log of calorie intakes, and log of food and non-food expenditure share to the total expenditures. Moreover, climatic norms such as rainfall and temperature shocks have adverse impacts on the household's well-being outcomes as well. The application of Binary Logit Model suggests that flood and climatic shocks have positive impacts on determining the poverty and food insecurity status of the households. However, in order to quantify the inequalities in the effects of the aforementioned covariate shocks, we have applied Generalized Ordered Logit Model on five ordered quantiles of the expenditures, monthly income, and calorie intakes by households. The results have established that covariate shocks are more hurting the lower quantiles, as compared to the higher quantiles of the expenditures, income, and calorie intakes.

Keywords: Climatic and Flood Shocks, Households' Well-being

3.1 Introduction

The underlying study aims at investigating the effects of the covariate shocks on households' welfare in Pakistan, which are highly vulnerable to climatic and natural disaster-prone threats. According to the Global Risk Index, Pakistan is holding the fifth position amongst the acrimoniously vulnerable countries. The economic losses of $ 3.8 billion are incurred during the last couple of decades as a result of climatic and flood disasters (Eckstein, Künzel et al. 2019). Likewise, (Watson, Lone et al. 2017) have suggested that Pakistan has been affected by a variety of covariate shocks which include high temperature and changing patterns of rainfall, cyclones, earthquakes, and droughts.

The documented literature also suggests that annually three million people are adversely affected by natural hazards. During the last four decades, only flooding has been incurring the economic losses of approximately 0.8% of GDP. Apart from natural disasters, macroeconomic shocks also have been producing negative impacts on the poorest and the highly vulnerable segments of the population. The exposure to above-mentioned covariate shocks is projected to be increasing over the time due to limited financial and institutional capacity of the country (Ali, Khan et al. 2020); (Watson, Lone et al. 2017).

The nexus between covariate shocks and households' well-being is well documented by available literature. (Heltberg and Lund 2009) have suggested that natural disasters have acrimoniously impacted the households' well-being in Pakistan. These adverse shocks have impacted the resilience power of the poor households. Apart from this, the prevailing financial constraints make them more vulnerable to the ongoing covariate shocks. So, these shocks push the ultra-poor households into the chronic poverty which further makes them highly exposed to the covariate shocks (Saeed and Hayat 2020); (Azeem, Mugera et al. 2019); (Kurosaki and Khan 2012).

Moreover, the literature has estimated the impacts of adverse shocks on households' livelihood and earnings in Pakistan. The natural hazards also damage the road, health, and education related infrastructure. As a result of all this, the vulnerable Labour force faces severe problems in the shape of loss of earning and livelihood opportunities. Consequently, poverty enhances and their well-being goes downward (Ali and Rahut 2020); (Jafar, Khalid et al. 2020); (Sher, Mazhar et al. 2018); (Ahmad, Mustafa et al. 2016); (Azeem, Mugera et al. 2016); (Deen 2015); (Haq 2015). Agriculture sector is one of the highly fragile sectors, as it has relation to the climatic and environmental hazards. This sector is highly important, in the context of Pakistan, because of two major reasons 1) it feeds the whole nation along with it, it also provides around 40% of Labour force, and 2) it also contributes 19% to the GDP. Agriculture sector is highly exposed to the risks of intensified rainfall patterns, floods, and cyclones, and these unexpected changing factors leave adverse impacts on the socioeconomic well-being of the households (Ullah, Apergis et al. 2020); (Deen 2015); (Haq 2015); (Ahmad, Mustafa et al. 2016).

The above discussion concludes that covariate shocks such as climatic, and flood shocks influence the households' well-being. But, the magnitudes of these shocks vary from region to region, and a lot depends on the adaptive capacity or resilience power of the households. The available literature has also suggested that those households who have low adaptive capacity or ability to cope with the shocks are considered as highly vulnerable households. Therefore, for empirical purpose, measuring the magnitude of shocks to the most vulnerable segment of the households is very important. Classifying the households by different income/expenditures, quantiles will help to estimate the magnitude of shocks, and which could help the policymakers in implementing effective targeting with respect to their vulnerability. Hence, the underlying study aims to test following hypothesis:

i) Whether covariate shocks influence the households' well-being or not

ii) To test the impacts of the shocks on different income/expenditures quintiles

3.1.1 Specified Objectives of Essay-1

This essay focuses on exploring the impacts of climatic and flood-prone shocks on households' well-being by using HIES 2018-19. Tehsil level covariate shocks are incorporated to investigate their impacts on households' well-being.

Following are the specified objectives:

1. To evaluate the impacts of climatic shocks (rainfall, flood, and temperature) on households' well-being indicators— per adult monthly expenditures, calorie intakes, monthly income and share of food and non-food expenditures to total expenditures.
2. To estimate the impacts of covariate shocks on household status i.e., poverty and food insecurity.
3. To explore inequalities of the impacts of covariate shocks across different quintiles of household expenditures, monthly income, and food security.

3.1.2 Significance of this Essay

The contribution of the underlying study has twofold: updating the existing literature, and policy implication. The available studies had estimated the impacts of one of the elements of natural disasters, like flood or rainfall by targeting the specific area or location. The current study is more comprehensive as it takes a very big sample i.e., 24809 households, from all the four provinces of the country, and it is an endeavor to merge the tehsil level shocks with the latest nationally representative household survey (HIES, 2018-19). It will help us to trace out the influences of the covariate shocks on multiple indicators of households' well-being. In addition to this, the study has employed climatic-prone shocks, which gives the insightful decomposition of the impacts of covariate shocks on household's welfare. Another most important contribution of the study is to unleash the inequalities of the influences of climatic and flood-prone shocks on food security, per adult expenditures, and monthly household income, share of food and non-food expenditures. The obtained findings of the study may be helpful to redesign available social protection programmes, which are presently working in country in order to mediate the adverse impacts of the aforementioned covariate shocks.

The subsequent part of the chapter comprises of section 3.2, which deals with the literature review, section 3.3 deals with the poverty dynamics in Pakistan, section 3.4 deals with the theoretical framework, section 3.5 deals with the methodological framework, section 3.6 deals with the results and discussion. Section 3.7 deals with the conclusion and policy implication of underlying study.

3.2 Brief Literature Review

Unexpected negative shocks have long-lasting implications on the socioeconomic well-being of the households in developing countries, especially those countries that are highly exposed to the natural hazards, such as Pakistan. The available literature has established the adverse influences of the covariate shocks like weather shocks, drought, flooding, cyclones, and earthquakes. Hence, this section sheds light on available literature relevant to covariate shocks and its influences on well-being.

Inflationary shocks are outcome of macroeconomic policy, which directly influence the well-being of the poor household. The literature in the context of Pakistan has documented the effects of inflationary shocks on different aspects of the household's well-being. (Ullah, Apergis et al. 2020) have estimated the impacts of inflationary shocks on economic growth and its impacts on the households' well-being in Pakistan. They have suggested that inflationary shocks leave adverse influences on the well-being of households which hurt the purchasing power of the poor households. The decline in household consumption has implication on the poverty status of the households. (Asghar and Naveed 2015) have explored the adverse impacts of shocks in petroleum and oil prices on the poverty and food security of the households. The estimated results are suggestive that it has increased the overall inflation in country which impacts the well-being of the poorest segment of the country. (Gazdar and Mallah 2013) have found the impacts of inflationary shocks on the food security of households. They suggested that inflationary shocks directly impact the purchasing power of the households, especially the food consumption which would impact the level of food security. Similarly, the literature is suggesting the adverse impacts of the inflationary shocks on the poverty, and food security level of the households in Pakistan (Hanif 2012); (Bukhari and Khan 2008); (Khalid, Malik et al. 2007).

Climatic and environmental shocks have significant influences on the well-being of the households in Pakistan due to their poor adaptive capacity against the occurring shocks. As the study conducted by (Sardar, Kiani et al. 2021) have explored the influences of the climatic shocks on the well-being of the farm households in

Pakistan. They have revealed that climatic shocks have significant impacts on the farm income of the households and it has significant implication on the level of food security and poverty. Similarly, (Ullah, Rashid et al. 2018) have estimated the adverse influences of the intense waves of the weather patterns which affect the health, food security, and wellbeing outcomes of the households in Pakistan.

(Ali and Erenstein 2017) has explored the impacts of the climatic shocks on poverty, food security, and livelihood opportunities of the households. The obtained findings of the study suggest that extreme events of weather have adverse influences on the level of poverty and food security. Moreover, these shocks are causing decline in employment opportunities. Likewise, (Ahmad, Mustafa et al. 2016) have estimated the counterfactual analysis of the climatic shocks on the food security of the farmers. They have explored that those households that have adapted the climatic shocks have higher level of food security. Hence, there is no dearth of the literature which has identified the adverse impacts of the climatic shocks on the well-being of the households in Pakistan, i.e., (Abid, Ali et al. 2020); (Ali 2018); (Kosec and Mo 2017). Similarly, the evidences from other developing countries also indicate the harmful impacts of covariate shocks on the well-being of the households (Anderson, Bayer et al. 2020); (Islam and Kieu 2020); (Kogo, Kumar et al. 2021); (Asfaw, Carraro et al. 2017); (Gregory, Ingram et al. 2005).

In sum, in the light of above discussed literature, our study contributes the literature to explore the impacts of all major tehsil level covariate shocks, such as rainfall and temperature, flooding, and inflationary shocks on poverty, food security, and monthly earnings of the households. Moreover, the study contributes by exploring the inequality in the impacts of the covariate shocks across different quantiles.

3.3 Poverty Dynamic in Pakistan

Designing social safety nets and National Finance Commission awards require the identification of poor in the country. Thus, estimation of poverty is vital in designing policy. Pakistan Bureau of Statistics and Planning Commission of Pakistan used food energy intake (FEI) method to estimate poverty till 2012. From 2013-14 Planning Commission of Pakistan is using cost of basic need approach to estimate poverty. In 2013-14 poverty line was drawn at 3030.32 per adult equivalent per month. Same poverty estimates were adjusted with consumer price index in 2015-16 at 3250 per adult equivalent per month. From Household Integrated Expenditure Survey 2018-19, poverty is estimated through cost of basic needs approach and poverty line is drawn at 3776 per adult equivalent per month. Poverty trends at national, provincial, urban and rural level are discussed below.

Table 3.1: Poverty Incidence

Area	2018-19 (Percentage point)	2015-16 (Percentage point)	Change in Poverty Percentage point
National	21.5	24.3	-2.8
Rural	27.6	30.7	-3.1
Urban	10.7	12.5	-1.8

*Taken from National Poverty Estimates (2020).

Table 3.1 shows that 21.5 percent households are below the poverty line at national level, showing 2.8 percent decline in poverty at national level. At rural level 27.6 percent households are below poverty line as compared to 30.7 percent in 2015-16. There is 3.1 percent decline in poverty from 2015-16 to 2018-19 at rural areas. At urban level 10.7 percent households are below the poverty line as compared to 12.5

percent in 2015-16. Data shows that decline in poverty is more pronounced in rural areas as compared to urban areas.

Table 3.2 shows that is gradual decline in poverty headcount since last decade. Poverty headcount has declined from 50.4 percent in 2005-6 to 21.5 percent in 2018-19. Similarly, there is decreasing trend of poverty head count at regional levels. In urban areas poverty headcount declined from 36.6percent to 10.7 percent in last HIES survey. In rural areas poverty headcount declined from 57.4 percent in 2005-06 to 27.6 in 2018-19. Interesting fact is, decline in poverty is more pronounced in rural areas as compared to urban areas. As higher number of workers from rural areas are working in middle east countries and higher portion of safety net (BISP) is going to rural households.

Table 3.2: Poverty Trends at National and regional Level 2005-06 to 2018-19

Poverty Incidence (%age points)				Change in Poverty (% age points)		
Year	**National**	**Urban**	**Rural**	**National**	**Urban**	**Rural**
2005-06	50.4	36.6	57.4	-	-	-
2007-08	44.1	32.7	49.7	6.3	3.9	7.7
2010-11	36.8	26.2	42.1	7.3	6.5	7.6
2011-12	36.3	22.8	43.1	.5	3.4	-1.0
2013-14	29.5	18.2	35.6	6.8	4.6	7.5
2015-16	24.3	12.5	30.7	5.2	5.7	4.9
2018-19	21.5	10.7	27.6	2.8	1.8	3.1

Source: National Poverty Estimates (2020).

Table 3.3 show the poverty trends at provincial level. Punjab is least poor province with 16.3 percent households below the poverty line. While Balochistan is the poorest among all province with 40.7 percent of households living below the poverty line. As Khyber Pakhtunkhwa witnessed terrorism in last decade, poverty has gone up in this province.

Table3.3: Poverty Trends at Provincial Level

Level	Poverty Incidence (Percentage Points) 2018-19			Poverty Incidence (Percentage Points) 2015-16			Change In Poverty		
	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural
Punjab	16.3	8.8	20.6	20.8	9.9	26.2	-4.6	-1.1	-5.5
Sindh	24.6	10.4	40	32.2	15.4	49.1	-7.6	-5.0	-9.0
KPK	27	16.8	29	18.1	10	19.9	8.9	6.8	9.1
Balochistan	40.7	24.7	46.7	42.2	26.4	48.2	-1.5	-1.7	-1.4
Pakistan	21.5	10.7	27.6	24.3	12.5	30.7	-2.9	-1.9	-3.0

Source: National Poverty Estimates (2020).

Poverty Bands divide population into different bands which need different policy initiatives. Thus poverty profile in terms of poverty bands is fruitful for policy makers. Table 3.4 shows poverty bands at national and regional level. Estimates shows that poverty bands changed slightly. Still 6 percent population is in extreme and ultra-poor category in 2018-19. Similarly, 16 percent population is poor and 20percent population is vulnerable to poor. In case of any shock (idiosyncratic or covariate) they will be below the poverty line.

Table 3.4: Poverty Bands at National and regional Level

Poverty Bands	2015-16			2018-19		
	National	Urban	Rural	National	Urban	Rural
Extreme Poor (below 50% of PL)	0.42	0.21	0.54	0.3	0.1	0.4
Ultra-poor (between 50 to75 % of PL)	6.00	2.39	7.95	5.2	1.9	7.1
Poor (between 75 to100 % of PL)	17.89	9.93	22.18	16	8.7	20.1
Vulnerable (between 100 to125 % of PL)	19.87	14.46	22.78	20	14.3	23.2
Quasi Non-poor (between 125 to 200 % of PL)	34.77	37.68	33.21	37.2	39.6	35.8
Non-poor (above 200% PL)	21.04	35.33	13.34	21.4	35.5	13.4
Total	100	100	100	100	100	100

Source: National Poverty Estimates (2020).

3.4 Theoretical Framework

This section replete with theoretical framework regarding the adverse impacts of covariate shocks. The framework is designed by two approaches: 1) simple flow chart, and 2) household’s utility function. Section 3.4.1 comprises the description of shocks and its impacts through flowchart, while section 3.4.2 explains the impacts of the shocks on households' utility function, which determines the households' welfare losses.

3.4.1 Conceptual Framework: Flowchart

There are two types of the shocks: covariate and idiosyncratic shocks. The latter is households-specific which may be due to loss of income, poverty, loss of job, death, and any other shocks are household-specific. The covariate shocks include, climatic-shocks (rainfall, and temperature), floods, cyclones, and storms, droughts and earthquakes. These shocks are not household-specific, but they influence the community on the whole. These shocks have significant and disastrous effects on the highly vulnerable segments of the society. The highly vulnerable households have poor adaptive capacity or they are poorly resilient against these shocks (IPCC, 2007; (Akhter and Basher 2014); (Anderson, Bayer et al. 2020).

In order to see whether people should be provided social assistance, so that they may be able to resist against occurring covariate shocks, IPCC (2007) has provided a comparison, if households' exposure to shocks is less than their adaptive capacity, then they do not need any assistance and they will manage the shocks by themselves. If households' exposure to shocks is equal to their adaptive capacity, then a little assistance is required to take them out of shocks (Lokonon 2019). Nonetheless, if households' adaptive capacity is lesser than their exposure to covariate shocks, then they are in dire need to receive social assistance to resist against the shocks. Hence, the highly vulnerable households may suffer welfare losses and become the victim of chronic poverty due to their susceptibility to the covariate hazards.

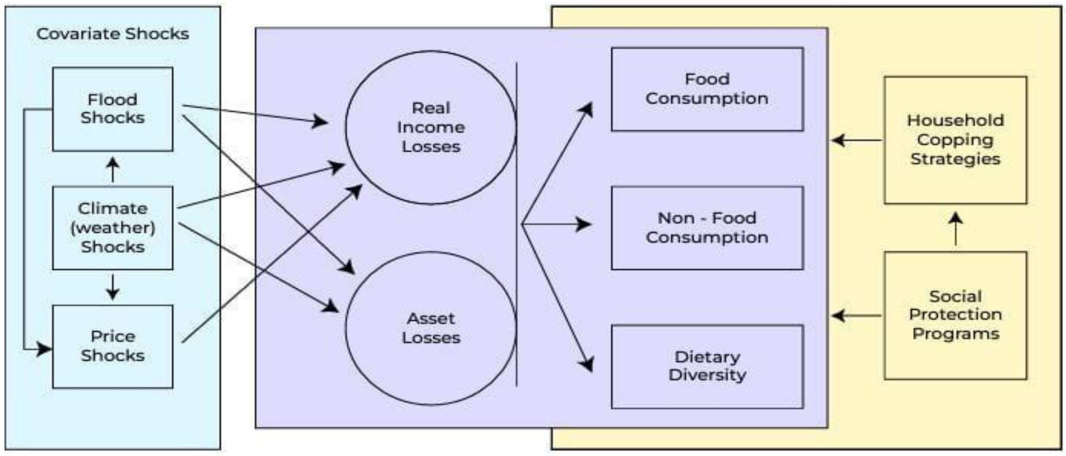


Figure-3.1: Conceptual Framework of the Impacts of Covariate Shocks on Households' Wellbeing (Asfaw, Carraro et al.2017).

Figure 3.1 comprises the framework of the impacts of covariate shocks on households' well-being. Covariate shocks such as weather shocks cause droughts and flood-prone disasters. These shocks further bring about price shocks apart from macroeconomic policy shift. Moreover, these shocks impact the real income and households' asset holding adversely, which in turn leaves acrimonious influences on food and non-food expenditures, and dietary intakes of the households (Asfaw, Carraro et al. 2017). Here, those households which have feasible and efficient adaptive capacity will be in a position to cope with the adverse impacts of the shocks. But those households which are highly exposed to these shocks are looking for some external support. The external support is mainly provided through the social protection programmes, such as conditional and unconditional cash transfer Programme (Deaton 1989); (Carter and Barrett 2006).

3.4.2 Household Utility Maximizing Approach and Covariate Shocks

The welfare losses due to climatic and flood-prone, and economic shocks are better understood by using the standard household's utility maximization model of microeconomic. The central aim is to formulate the mathematical model to frame up the impacts of the covariate shocks through household's utility maximization approach. Firstly, we derive it when we assume households are facing no shocks, then, we include the shocks in model to frame up the adverse influences of the shocks.

In order to design the theoretical framework to estimate impacts of shocks in the context of household utility function, let's assume that household's utility function depends on two types of goods— food (C_f) and non-food (C_{nf}) goods. It is assumed that utility function of the households is similar, but they are not similar to their socioeconomic characteristics, that are denoted by a vectorZ_i. Such vector includes the factors like household head specific factors (age, gender, marital status, education, and employment of household head), and household based factors, household size, dependency ratio, and household assets, and housing quality (Barrett, Reardon et al. 2001); (Ashraf and Routray 2013); (Deaton 1989). Hence, households' utility function is written as follows:

$$U_{ij} = U(C_f, \quad C_{nf} \mid \quad z_i) \tag{3.1}$$

Above equation indicates that households are seeking utility from food and non-food goods given their socioeconomic background, and we assume that households do not face any covariate shocks. So, the model works with simple households' utility-function settings. Moreover, it is assumed that in a static setting, a household maximizes its utility by keeping in view its budget constraints. The socioeconomic differences determine the buying power of the households. A low-income earning household faces many constraints to maximize its utility, and high-income group households may have relatively lower constraints on their budgetary allocation. Given such limitations, a household has to choose how to allocate their income and available resources in order to maximize its utility. Hence, the budget line is specified as follows:

$$p_f C_f + p_n C_{nf} = m_i \quad (3.2)$$

In the above equation, m_i is households' income which they earn from farm and non-farm sectors. Similarly, p_f and p_n indicate prices of food and non-food goods. Assume that these prices are same across the locations, for simplicity.

So, equation 3.2 can be written as follows:

$$m_i\text{-}(p_f C_f + p_n C_{nf}) = 0 \quad (3.3)$$

The equation 3.3 indicates the budget line for the utility maximizing household.

We have described the utility function and budget constraint of the utility maximizing household. So, the formulation of the function is described as follows.

The lagrangian function is

$$L = U(C_f, \quad C_{nf} \mid \quad z_i) + \lambda[\, m_i\text{-}(p_f C_f + p_n C_{nf})] \quad (3.4)$$

By solving above equation we get demand functions of food and non-food goods. By substituting these demands functions in the objective function we get indirect utility function, which depends on prices, and income of the households, given its other socioeconomic factors.

Then we applied Roy's Identity

$$C_f = -\frac{\frac{\partial V}{\partial p_f}}{\frac{\partial V}{\partial m_i}} \mid \; z_i \quad (3.5)$$

we obtained the Marshallian demand for the food goods, which depends on price, and income of the households, given his other socioeconomic factors. Similarly, through Roy's Identity we obtained Marshallian demand for non-food goods.

$$C_{nf} = -\frac{\frac{\partial V}{\partial p_n}}{\frac{\partial V}{\partial m_i}} | \quad z_i \tag{3.6}$$

To sum up the discussion, we have derived the demand function of the food and non-food items that depend on price level and households' income. These settings are derived by assuming that households are not facing any covariate shocks.

In the last discussion of the household utility function, we have assumed the absence of the covariate shocks like inflationary shocks, climatic and flood-prone shocks. And, we have established through Figure 3.1 that covariate shocks have adverse impacts on food and non-food consumption, and ultimately it impacts the dietary intakes and health outcomes (Lim 2017). Now, we include these shocks aforesaid utility function. The standard microeconomic modeling of consumer behavior has suggested that demand of a quantity is negatively influenced by the own prices, which means the increase in prices will decrease the demand vice versa. And, income has positive impacts on the demand of quantity demanded vice versa. It means any change or shock in prices and income of the households will affect the demand, because it directly and indirectly affects the budget line of the households.

We assume that households are exposed to two types of shocks: economic, and environmental. The economic shock, which directly impacts the households' well-being, is inflationary shock. Such shock is the outcome of the disruption in macroeconomic policy shifts. As we have discussed before, that inflation will contain the budget line further $(p_f C_f + p_n C_{nf} = m_i)$, and it will cause decline in real income of the households as we have established in the Figure 3.1. The environmental shocks include weather shocks and flood-prone hazards. These shocks have caused adverse impacts on the households' assets and real income ((Lim 2017); IPCC, 2019). So, we have the following equation for shocks adjusted budget line as follows:

$$S = s(W, F) \tag{3.7}$$

In the above equation, S indicates the occurrence of covariate shocks, W=weather shocks, and F=flood-prone shocks. And, "s" is the factor which suggests the intensity of the covariate shocks. We assume that shock occurs in a particular time, which is static. The exposed households may have new budget line which is shock adjusted, given as follows.

$$S\ [p_f C_f + p_n C_{nf} = m_i] \tag{3.8}$$

Above equation indicates, the households' budget line is influenced by the happening of any of the shocks (weather shocks, and floods). How much it will be damaging completely depends on the magnitude of the shocks. If, S>$[p_f C_f + p_n C_{nf} = m_i]$, then budget line will be negative i.e., $m_i - (p_f C_f + p_n C_{nf}) < 0$. This equation indicates that households have poor resilience power to confront occurring shocks, which highlights that households have poor adaptive capacity. As equations 3.5 & 3.6 have established that changes in prices and income will have significant impacts on the demand of food and non-food commodities. It further implies that these adverse shocks could have negative impacts on the welfare of the households—food security, and poverty etc. Alternatively, if S<$[p_f C_f + p_n C_{nf} = m_i]$, then it indicates that shocks are not enough disastrous to significantly influence the budget line, which implies that these households may have higher ((Ansah, Gardebroek et al. 2021); (Dhanaraj 2016); (Mitra, Palmer et al. 2016)) resilience power because they can cope with shocks by opting multiple forms of coping strategies, because they have higher adaptive capacity ((Ansah, Gardebroek et al. 2021); (Ahmad, Mustafa et al. 2016); IPCC, 2007)).

By concluding the discussion, the on-going study mainly follows the literature how it conceptualizes the linkages between covariate shocks and household well-being. The main contribution of the study is that we have included all types of possible shocks such as rainfall, temperature, flood, and macroeconomic shocks in the framework of utility maximization, while to the best of my knowledge, the available literature only includes idiosyncratic shocks in the utility maximization framework.

Above discussion implies that those households that are poor and have poor adaptive capacity will be highly exposed to the covariate shocks. They need social protection to cope with these shocks. As in the case of Pakistan, BISP is one of the largest social safety nets which has potential to help the poor households to cushion the adverse impacts of covariate shocks. (Watson, Lone et al. 2017) has suggested that BISP has very extensive and community-based infrastructure. It should be redesigned to launch programmes for weather and flood-prone hazards.

3.5 Methodological Framework

This section deals with discussion on the source of data, and variable construction, and methodological framework of the study.

3.5.1 Data Source

The underlying study has used three sources of data to accomplish the specified objectives. Primarily, analysis is based on Household Integrated Expenditure Survey (HIES) 2018-19, which nationally representative household survey, and it is conducted by Pakistan Bureau of Statistics. The sample we have is 24,809 households from four provinces (Punjab, KPK, Sindh, and Balochistan). From HIES, we have estimated the well-being indicators of the households, while other socioeconomic profile of households is measured from this household survey. The data of tehsil level flood water covering area square kilometer is collected from NASA MODIS Satellite Data, whereas, tehsil level climatic data of rainfall and temperature is taken from European Center for Medium-Range Weather Forecasts (ECMWF). We have collected the data of tehsil level. In order to merge it with tehsil's information, we have obtained the code classification of tehsils available in HIES. After identification of tehsils from HIES household survey data, we merged all flood and climatic variables by using tehsil codes as key identifier.

3.5.1.1 Variable Description

From HIES, we have obtained 5 dependent variables which determine the household's well-being. Such indicators include per adult monthly expenditure (PKR), household monthly income (PKR), share of non-food expenditures to total expenditures, share of food expenditures to total expenditures, and per adult calorie intakes. The description of such variables is presented as follows:

Per Adult Equivalent Expenditures: This variable is constructed by collecting the information of household expenditures from HIES, consumption module; by aggregating the household expenditures and divided it by per adult family size. Households above 15 years are assigned score 1, while below 15 years, we assigned score 0.8, and aggregating these with respect to households we obtained per adult equivalent household size. So, we measure per adult equivalent monthly expenditures at household level. This variable is commonly taken as the indicator of households' well-being or welfare (Government of Pakistan, 2016).

Poverty Status: Poverty status is measured from per adult equivalent expenditures on the basis of cost of basic need (CBN) approach where 1 is assigned, if households are consuming below PKR 3,776, per adult monthly expenditures are considered as poor household, while 0 is assigned for non-poor households. This is official poverty line which is now being used by researchers (Government of Pakistan. 2016); (Tasos, Amjad et al. 2020).

Share of Non-food, and Food Expenditures to Total Expenditures: From consumption modules, we have used aggregated non-food expenditures, and then these expenditures are divided by total household expenditures. Similarly, total food expenditures made by a household are divided by total expenditures. This provides us the share of food expenditures to the total household expenditures. These two variables are employed separately as the measure of well-being.

Per Adult Daily Calorie Intakes: Calorie intakes are computed from food quantity consumed by a household. The quantities consumed are converted to daily basis, and then each quantity consumed is multiplied by the recommended calorie available in particular food items. The obtained calorie intakes are aggregated at household level, and then it is divided by per adult equivalent family size. The resultant outcome is per adult equivalent calorie intakes which a household is consuming at daily basis. This is the most usable methodology of computing calorie intakes, especially academic research due to its simple methodology and availability of the data. As (Ahmad, Mustafa et al. 2016) have employed this methodology to compute calorie intakes of the farm households in Pakistan. Computation of the calorie intakes have some alternative methodologies, like (Lim 2017) based methodology which computed minimum dietary energy requirement (MDER) which is dependent on households' demographic-composition.

Food Insecurity Status: Food insecurity is measured by binary variable where food insecurity is assigned 1, if a household is taking less than 2350 calorie intakes daily, while 0 is assigned if a household is in-taking calories above specified threshold level.

Government of Pakistan has recommended this threshold. Although, this threshold is being debated now, but still at official level, this cut-off is being used to compute food poverty.

Household Monthly Income: Household monthly income is obtained from all sources of the income received by all family members. The obtained income is aggregated at household level, which is obtained from all sources, agriculture and non-agriculture.

Inequalities in Expenditures, Income, and Calorie Intakes: The inequalities in household expenditures, income, and calorie intakes are measured by generating the five quantiles. Such quantiles are ordered from the lowest to the highest quantile. These quantiles are used to estimate the impacts of the shocks on inequalities in expenditures, income, and calorie intakes separately. Such specifications are used by (Alamgir, Furuya et al. 2021).

Table 3.5: Brief Description of the Variables

Dependent Variables	**Description of Variables**	**Unit**
Per adult expenditures	Total monthly household expenditures are divided by per adult score	PKR
Per adult calorie intakes	Food quantity consumed is multiplied by respective calorie recommended for food items and divided by per adult score	KC
Share of non-food expenditure	Total non-food expenditures divided by total expenditures	Ratio
Share of food expenditure	Total food expenditures divided by total expenditures	Ratio
Monthly household income	Monthly income earned from all sources by households	PKR
Poverty status	1 is assigned to poor, if household is spending below PKR 3776, and 0 otherwise for non-poor households	Binary
Food insecurity status	1 is assigned if household is having calorie intakes per adult daily below 2350, it is termed as food insecure, and 0 otherwise	Binary
Inequalities in expenditures	Five quantiles of expenditures from lowest to the highest	Categorical
Inequalities in calorie intakes	Five quantiles of calorie intakes from lowest to the highest	Categorical
Inequalities in income	Five quantiles of income from lowest to the highest	Categorical
Independent Variables		

Flood shocks	Deviation of long run average from current period	Sq. km
Rainfall shocks	Deviation of long run average from current period	Ml
Temperature shocks	Deviation of long run average from current period	C^0
Control Variables		
Employment status	Binary variables for agriculture, self-employed, and paid employee	Binary
Age	Age of household head in completed years	Years
Gender	1 is assigned to male, 0 for female (household head)	Binary
Marital status	1 is assigned if head is married, and 0 otherwise	Binary
Flush wash room	1 is assigned if household has flush toilet, 0 otherwise	Binary

Covariate Shocks: Covariate shocks are measured in three ways: climatic variables such as temperature and rainfall shocks, and flood shocks at tehsil level. (Asfaw et al. 2017), (Watson et al.2017).

Flood shocks are measured through the water that covers the square kilometer area. We have used the deviation of current period flood situation from long run average water coverage by flood. Likewise, we have used average flood water coverage by area square kilometer is employed as the control variable along with flood shock variable. A map is presented in appendix, which highlights the risk factor of flood shocks.

Climatic factors such as rainfall and temperature shocks are measured as we have measured the flood shock by deviating the long run average from current year rainfall and temperature norms separately. The mean deviation provides us the estimates of the climatic shocks. Map of rainfall and temperature shocks is given in appendix, which is borrowed from the website of Pakistan Metrological Department (PMD). Such indicators of the climatic variables are employed by (Ahmad, Mustafa et al. 2016) & (Asfaw, Carraro et al. 2017).

Control Variables: Control variables such as household head characteristics (age, education, employment status, and gender) and other household level elements (dependency ratio, and family size), and regional (rural and urban) and provincial dummies (Punjab. KPK, Sindh, and Balochistan) are constructed from HIES 2018-19. The detailed description of such variables is presented in Table-1. These control variables will help to trace out the actual impacts of the covariate shocks on the households' well-being. Household-specific control variables will be helpful cover the household related differences in model ((Ahmad and Farooq 2010); (Ahmad and Afzal 2021)), while regional and provincial dummies will be helpful to capture the locational differences. Although, covariate shocks are based on tehsil levels, but these variables will be significantly important to estimate the locational differences. For tehsil level differences, the robust standard error will be clustered on the basis of tehsils of the households. The descriptive statistics of all these variables is given in table 3.6.

Table 3.6: Descriptive Statistics from HIES (2018-19)

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Outcome Variables					
Dietary Intake	24,809	2356.66	780.64	593.83	22958.09
Food Insecure	24,809	0.57	0.49	0.00	1.00
Poverty Status	24,809	0.18	0.39	0.00	1.00
Log per adult expenditures	24,809	8.66	0.49	7.12	12.38
Household Characteristics					
Head age	24,809	45.84	13.61	16.00	99.00
Head gender	24,809	0.91	0.29	0.00	1.00
Head married	24,809	0.98	0.15	0.00	1.00
Dependency ratio	24,809	1.00	0.79	0.04	7.00
Livestock	24,809	0.23	0.42	0.00	1.00
Agriculture	24,809	0.18	0.38	0.00	1.00
Self-employed	24,809	0.17	0.37	0.00	1.00
Paid-employee	24,809	0.47	0.50	0.00	1.00
Rooms per member	24,809	2.36	1.38	1.00	15.00
Improved Water	24,809	0.63	0.48	0.00	1.00
Flush Toilet	24,809	0.76	0.42	0.00	1.00

Climatic Shocks					
Average Flood	24,663	0.03	0.04	0.00	0.32
Flood Shock	24,663	-0.25	0.24	-0.63	3.88
Rainfall Average	24,663	1.65	1.45	0.17	5.47
Rainfall shock	24,663	-1.90	0.75	-4.38	-0.67
Average Temperature	24,663	28.23	4.92	-0.96	34.56
Temperature Shock	24,663	-27.44	4.82	-33.31	0.66

3.5.2 Empirical Methodology

As we have discussed that the primary objective of the underlying study is to explore the impact climatic and flood-prone shocks on the welfare of the households in Pakistan. For empirical purpose, the existing literature has suggested the application of the OLS, and Logit Model Type approaches to quantify the impacts of climatic and flood-prone shocks on the well-being of the households (Markhvida, Walsh et al. 2020); (Venkataramanan, Packman et al. 2019); (Baez, Lucchetti et al. 2015). It mainly depends on the setting of the dependent variables. So, in this study, we have three types of setting of the dependent variables: continuous, binary, and ordered in categories. The specifications of models for these three types of dependent variables are discussed as follows:

When we have continuous dependent variables such as: log of per adult equivalent monthly expenditures, 2) log of household monthly income, 3) log of per adult equivalent calorie intakes, 4) log of share of food expenditures to total expenditures, and 5) log of share of non-food expenditures to total expenditures, in order to estimate the effects of shocks on households' wellbeing, the specification of the model is specified as follows.

$$logY_i = \beta_0 + \gamma_i CS_i + \beta_i X_i + \mu_i \tag{3.9}$$

Where i=1, 2, 3….., n

To check the impact of shocks separately (only shock in model)

$$logY_i = \beta_0 + \gamma_i CS + \beta_i X_i + \mu_i \quad \text{………………………………….. (3.10)}$$

In above equation 3.9, $logY$ is indicated for log of dependent variables, and we have five dependent variables as discussed above. For these mentioned dependent variables, each model is estimated separately with same specification. Moreover, CS_i variable indicates the vector of covariate shocks. Such shocks include climatic shocks includes rainfall, and temperature shocks along with their long run averages, and flood shocks. These covariate shocks are expected to impact adversely the well-being of the households (dependent variable) as we described the conceptual framework in section 3.4. Finally, vector X_i suggests the set of control variables which include the household head related (age, gender, marital status, and employment status), and household specific variables such as dependency ratio, family size, and having flush toilet, and finally regional (rural, and urban), and provincial dummies for Sindh, KPK, and Balochistan, while Punjab is set as the reference category.

The above specification will be estimated by using OLS, in order to estimate the impacts of the covariate shocks on the well-being of the households. Moreover, we would apply quantile regression model to disseminate the impacts of covariate shocks across the quantile (25^{th}, 50^{th}, and 75^{th}). The quantile regression will help to understand that what happened to the impacts of shocks on log of per adult equivalent monthly expenditures, log of household monthly income, and log of per adult equivalent kilo calorie intakes, if we apply the quantile regression with respect to different quantiles.

The other reason to apply the quintile regression is that behavior of consumption and calorie intakes varies across different quintiles, such as the poorest is expected to have relatively lower intake of calories, while the richest have higher level of calorie intakes. So, applying the mean approach which usually OLS is assumed to have, could give biased impacts due to the presence of the outliers in the model. So, the quintile regression is supposed to be the solution of such framework of the econometric model (Cameron, A. C., & Trivedi, P. K. 2005).

The objective of the application of this technique is to document the inequalities in the impacts of the climatic shocks on different (25^{th}, 50^{th}, and 75^{th}) quantile groups of the households.

After above-mentioned five indicators of the well-being, the underlying study has specified the models for poverty and food insecurity status respectively. These two variables are in binary nature, where poverty status contains, 1 is assigned to poor household and 0 otherwise. Likewise, food insecurity status is defined as binary (1=food insecure households, and 0 otherwise). The heaps of literature have suggested the implementation of the Binary Logit Model.

Hence, the study has estimated the impacts of covariate shocks on both poverty and food insecurity status separately. The specification of these models is presented as follows:

$$Z_i(1 = poor, and\ 0\ otherwise) = \beta_0 + \gamma_i CS_i + \beta_i X_i + \mu_i \tag{3.10}$$

Where i=1, 2, 3….., n

In equation (3.10), rest of the specification remains same as in the case of equation (3.9), only the structure of dependent variable is changed. Z_i, variable indicates a binary form of dependent variable for both poverty status and food insecurity status, and these two models are estimated separately by using the Binary Logit Model, where if γ_i>0 would identify the adverse impacts of the covariate shocks on both poverty and food insecurity.

Moreover, the study intends to identify the impacts of covariate shocks on the inequalities in per adult expenditures, monthly household income, and calorie intakes. For this purpose, the study has classified each mentioned variables into five quantiles, which covers the inequalities from the lowest (1st) to the highest (5th). Such classifications contain the ordering in the household expenditures, income, and calorie intakes. The specification of such models is given as follows:

$$Q_i = \beta_0 + \gamma_i CS_i + \beta_i X_i + \mu_i \tag{3.11}$$

Where Q_i is an ordered categorical variable, where 1 for the lowest quantile (1st), 2 for second, 3 for third, 4 for fourth, and 5 for fifth quantile. Here, fifth quantile (the highest) for each outcome such as expenditures, income, and calorie intakes is kept as the reference category. Three models will be estimated separately for each outcome variable. The rest of the specification of the equation (3.11) is same as the case of equation (3.10).

Hence, in such cases, Ordered Logit Model is preferred to multinomial Logit. So, the Ordered Logit Model has assumption of parallel regression. This assumption is tested by applying Brant Test. The Brant test suggests: H_0 (null hypothesis) contains the presence of parallel regression, while H_a specifies the violation of parallel assumption in Ordered Logit Model. This means that the statistical significance of the Brant test would recommend the violation of the parallel regression assumption. However, the alternative solution is application of the Generalized Ordered Logit (GOL) model

(Marcoux, Yasmin et al. 2018); (Williams 2016); (Eluru and Yasmin 2015); (Abegaz, Berhane et al. 2014).

For empirical purpose, we have applied Brant test after the application of Ordered Logit Model, we have found that parallel regression assumption is violated. Hence, we have applied GOL model to estimate the impacts of the covariate shocks (inflation, flood, and climatic norms) on the inequalities in per adult equivalent expenditures, household monthly income, and per adult calorie intakes.

It is assumed that all households who are living in sampled tehsils are equally exposed to the climatic shocks. The vulnerability to the flood, and climatic shocks depends on the variability of the sensitivity of the particular geographical location. Hence, in the setting of all empirical models specified as given in above-description are assuming all households in particular location are equally exposed to the covariate shocks.

3.6 Results and Discussion

This section is replete with discussion on estimated results for the impacts of climatic and flood shocks on the households' well-being in Pakistan. Well-being is measured by five indicators, income and consumption-based indicators such as log of per adult monthly expenditures, log of calorie intakes, log of food expenditures share out of total expenditures, log of non-food expenditures out of total expenditures, and log of monthly households' income. Households' monthly income measures the outcome of livelihood and employment. Hence, these six indicators are employed as outcome variables to estimate the impacts of covariate shocks (climatic and flood). Moreover, we have classified the poverty status (1= poor, 0 for non-poor), and food insecurity status (1=food insecure, and 0 for food secure households), while to observe the impacts on income, calorie intakes, and expenditures inequalities; we have employed the five quantiles with respect to income, calorie intakes, and per adult expenditures. Moreover, we have estimated all models by using single shock in each model, which we have given the results description in Appendix. So, the discussion on the estimated results is exhibited as follows:

3.6.1 Impacts of Covariate Shocks on Overall Households' Well-being

We have used two sorts of covariate shocks: 1) weather shocks (Rainfall and temperature shocks), and 2) flood-shocks. The shocks are measured by mean deviation from long run averages, while simple linear terms are used as the control variables related to the respective weather and flood shocks. Likewise, households' socioeconomic characteristics such as head age, education, gender, and employment status, and family size, dependency ratio, and regional and provincial dummy variables are employed as the control variables. And, aforementioned five indicators of well-being are employed as the dependent variables separately.

Table 3.7: Impact of Covariate Shocks on Households' Well-being

Variables	Log PAE expenditure	Log PAE calorie intakes	Log Household monthly income	Log of share of non-food expenditure	Log of share of food expenditure
Average flood	-0.248***	-0.372***	-0.488***	-0.0843**	0.0953**
	(0.0661)	(0.0450)	(0.100)	(0.0346)	(0.0426)
Flood shock	-0.0169	-0.0205***	-0.0315*	-0.0115*	0.00718
	(0.0103)	(0.00613)	(0.0167)	(0.00624)	(0.00718)
Average rainfall	0.0307***	0.0105***	0.0352***	0.0181***	-0.0323***
	(0.00604)	(0.00396)	(0.00962)	(0.00294)	(0.00407)
Rainfall shock	-0.0173***	0.0320***	-0.0157	-0.00672**	-0.0126***
	(0.00621)	(0.00398)	(0.0102)	(0.00286)	(0.00403)
Average temperature	-0.0883***	0.0660***	-0.0929***	-0.0143**	0.0268***
	(0.0111)	(0.00764)	(0.0172)	(0.00601)	(0.00767)
Temperature shock	-0.0858***	0.0684***	-0.0932***	-0.0211***	0.0356***
	(0.0112)	(0.00768)	(0.0174)	(0.00607)	(0.00779)
Prices (Paasche index)		-0.0497*			
		(0.0268)			
Head agriculture	0.0263***	0.0647***	0.180***	-0.0448***	0.0619***
	(0.00958)	(0.00613)	(0.0192)	(0.00467)	(0.00622)
Head self-employed	-0.0184*	0.00660	0.344***	-0.00928**	0.0189***
	(0.0105)	(0.00655)	(0.0185)	(0.00449)	(0.00667)
Head paid employee	-0.119***	-0.0416***	0.245***	-0.0270***	0.0389***
	(0.00911)	(0.00568)	(0.0174)	(0.00399)	(0.00580)

Household size	-0.0520***	-0.0303***	0.0891***	- 0.00234***	0.00458***
	(0.00119)	(0.000718)	(0.00164)	(0.000442)	(0.000577)
Head age	0.00286***	0.00312***	0.00724***	0.000164	-0.000657***
	(0.000225)	(0.000147)	(0.000389)	(0.000107)	(0.000143)
Dependency ratio	-0.0895***	-0.0782***	-0.188***	-0.0193***	0.0265***
	(0.00366)	(0.00248)	(0.00658)	(0.00175)	(0.00228)
Head gender	-0.0710***	-0.0413***	0.638***	-0.00901*	0.0132*
	(0.0113)	(0.00703)	(0.0284)	(0.00484)	(0.00713)
Head married	-0.136***	-0.138***	-0.0242	0.0117	0.000519
	(0.0196)	(0.0138)	(0.0306)	(0.00975)	(0.0130)
Flush toilet	0.205***	0.0578***	0.238***	0.0978***	-0.0945***
	(0.00614)	(0.00426)	(0.0101)	(0.00366)	(0.00416)
Region (1=rural, 0=urban)	-0.220***	0.00139	-0.240***	-0.0715***	0.109***
	(0.00655)	(0.00410)	(0.00976)	(0.00299)	(0.00424)
Sindh	-0.00217	0.0388***	-0.0104	-0.0826***	0.100***
	(0.00898)	(0.00577)	(0.0139)	(0.00468)	(0.00581)
KPK	-0.137***	0.0976***	-0.262***	-0.0335***	0.0738***
	(0.0148)	(0.00944)	(0.0243)	(0.00711)	(0.00985)
Balochistan	-0.0488***	0.0283***	-0.0382**	-0.0625***	0.0793***
	(0.0134)	(0.00901)	(0.0194)	(0.00723)	(0.00932)
Constant	8.902***	8.068***	9.632***	3.485***	4.450***
	(0.0621)	(0.0419)	(0.102)	(0.0314)	(0.0404)
Observations	*24,663*	*24,663*	*23,072*	*24,663*	*24,663*
R-squared	*0.375*	*0.231*	*0.390*	*0.234*	*0.226*
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					
Impact of covariate on five different indicators of household well-being are estimated through OLS. Flood, rainfall and temperature shock are negatively impacting household well-being.					

Table 3.7 encompasses the empirically obtained results through the application of OLS. The results suggest that flood-shocks are having the significant and negative impacts on all indicators of the well-being except log of food share in total expenditures. The estimated results indicate that as the flood shocks events worsened, households of affected areas are facing the loss of well-being of households in Pakistan by 1% to 3%. The results demonstrate that households bear loss of per adult expenditures by 1%, calorie intakes by 2%, monthly income by 3%, and share of non-food expenditures by 1% while insignificant impacts on share of food expenditures.

The influences of linear term of long run average of flood have much stronger and significant influences on all 5 indicators. The overall results imply that although flood shocks cause reduction in overall expenditures and calorie intakes, households increase their proportion of food expenditures to maintain their dietary intakes. Such implications are reflected through the negative and significant impact of long run average flood occurrence. As we have discussed that flooding variable is measured by the area of locality covered by flood water. This indicates that as the higher quantity of water comes and it covers higher area square meter, it impacts adversely the households' welfare indicators on the whole. The adverse impacts of flood-prone disasters are documented by literature (Asfaw, Carraro et al. 2017); (Firdaus, Senevi Gunaratne et al. 2019); (Khayyam and Noureen 2020).

The effects of the climatic variables on households' well-being indicators are estimated statistically and significantly. The rainfall shocks have negative and significant influences on log of per adult expenditures, log of household income, and share of both food and non-food with total expenditures. These income and expenditures related indicators are directly and indirectly measure of the households' welfare, and these are expected to be adversely affected by the rainfall shocks. On average, the loss of welfare is estimated by 1% to 2% due to rainfall shocks. The simple long run average of the rainfall has positive impacts on all well-being indicators except share of food expenditures (Table 3.7). Only log of calorie intakes is affected positively. The positive impacts of only rainfall while keeping other factors constant, indicates that increase in rainfall norms may give higher agriculture food productivity which ultimately has positive effects on the food availability. The adverse effects of flooding on calorie intakes may suggest that if higher and intense patterns of rainfall result in flooding, then it will leave adverse effects on calorie intakes. Similarly, temperature shocks also have negative effects on all other welfare indicators except calorie intakes. In a nutshell, overall, the effects of climatic shocks and flood shocks are adversely affecting the households' well-being (Table 3.7).

These adverse impacts of the climatic shocks are supported by the literature regarding Pakistan. As the study conducted by (Ahmad, Mustafa et al. 2016) have estimated the adverse influences of the climatic shocks on food security and farm productivity of the farm households in Pakistan.

Table 3.7A (see appendix) provides the estimated impacts of only flood shocks along with same socioeconomic control variables on households' welfare indicators and Table 3.7B (see appendix) contains the estimated impacts of the climatic shocks on welfare indicators. On the whole, results remain robust. In terms of sign and significance, impacts of both flood shocks and climatic shocks are similar to the Table 3.7. These results are compatible with the findings of literature (Asfaw, Carraro et al. 2017).

Apart from these shocks given in Table 3.7, we have estimated separate models for each shock, such estimation for flood shock rather than all shocks variables is included in single model (see Appendix 3.7A & 3.7B). The findings of all shocks are found robust in terms of sign and direction of the coefficients.

Apart from covariate shocks, households' socioeconomic elements are also used as the control variables which have significant influences on the well-being of households. Such elements include head gender, age, education, and employment status, while family size and dependency ratio also have the significant impacts on households' well-being (Table 3.7).

3.6.2 Impact of Shocks on Poverty and Food Insecurity Status of Households

After tracing out the impacts of covariate shocks on five indicators of households' well-being, the underlying study has estimated the impacts of shocks on poverty and food insecurity status of the households by using Binary Logit Model. Households' poverty status is a binary variable where 1 is assigned to the poor household, while 0 is assigned to non-poor. Likewise, binary variable of food insecurity is indicated that 1 is assigned if household is found having daily calorie intakes below 2350 calories per adult, 0 is assigned otherwise. Hence, the positive sign of shocks on both outcome variables will indicate the adverse effects of shocks on the poverty and food insecurity status.

Table 3.8 presents results obtained from Binary Logit Model along with estimation of odd ratios and marginal effects to interpret the magnitudes of the coefficients. Empirically obtained results are suggestive that flood shocks have adverse impacts on the household’s poverty and food insecurity status. The positive sign indicates that other things remain constant, the increase of flood water is more likely to bring about increase in poverty and food insecurity. Moreover, the long run norm of average flood water has much stronger implication on both poverty and food insecurity of households. These findings also substantiate the previously discussed findings regarding flood events. The marginal effects indicate that on average, average flood norm is more likely to impact adversely by 11 percent to poverty, while the probability to increase the food insecurity increases by 56 percent, which demonstrates that flood occurrence severely hits the household well-being. Moreover, flood shock is measured by the deviation from long run mean also demonstrates the adverse impacts on food insecurity and poverty status of the households. The available literature also shows the adverse impacts of flood-prone disasters on food insecurity in Pakistan. As the study conducted by (Ahmad and Afzal 2021) have estimated the adverse impacts of floods on food insecurity through displacement in rural areas of Pakistan.

Table 3.8: Impact of Shocks on Household Wellbeing: Logit Estimation

	Poor=1, 0=Non-Poor			**Food Insecure=1, 0= Food Secure**		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	**Logit**	**Odd Ratio**	**Marginal**	**Logit**	**Odd Ratio**	**Marginal**
Average Flood	1.018**	2.766**	0.1132***	2.363***	10.62***	0.5694***
	(0.511)	(1.414)	(0.057)	(0.409)	(4.347)	(0.099)
Flood shock	0.169**	1.184**	0.0188**	0.153**	1.166**	0.0369**
	(0.0721)	(0.0854)	(0.008)	(0.0618)	(0.0721)	(0.015)
Average Rainfall	-0.105**	0.900**	-0.0117**	-0.0975***	0.907***	-0.023***
	(0.0484)	(0.0436)	(0.005)	(0.0345)	(0.0313)	(0.008)
Rainfall Shock	0.201***	1.223***	0.0224***	-0.205***	0.815***	-0.049***
	(0.0476)	(0.0582)	(0.006)	(0.0334)	(0.0272)	(0.008)
Average Temperature	0.557***	1.745***	0.0619***	-0.450***	0.638***	-0.108***
	(0.0847)	(0.148)	(0.009)	(0.0675)	(0.0431)	(0.016)
Temperature shock	0.504***	1.655***	0.0561***	-0.464***	0.629***	-0.112***
	(0.0850)	(0.141)	(0.008)	(0.0682)	(0.0429)	(0.016)
Agriculture employment	-0.531***	0.588***	-0.0521***	-0.520***	0.594***	-0.127***
	(0.0793)	(0.0466)	(0.007)	(0.0549)	(0.0326)	(0.014)
Self-employed	-0.171**	0.843**	-0.0182***	-0.0744	0.928	-0.018
	(0.0844)	(0.0711)	(0.009)	(0.0554)	(0.0514)	(0.013)
Paid-employee	0.324***	1.382***	0.0363***	0.242***	1.273***	0.058***
	(0.0717)	(0.0991)	(0.008)	(0.0476)	(0.0606)	(0.011)
Household size	0.226***	1.253***	0.0251***	0.266***	1.305***	0.064***
	(0.00734)	(0.00920)	(0.001)	(0.00752)	(0.00981)	(0.002)
Head age	-0.0117**	0.988***	-0.0013***	-0.0223***	0.978***	-0.005***
	(0.00168)	(0.00166)	(0.002)	(0.00126)	(0.00123)	(0.001)
Dependency ratio	0.522***	1.685***	0.0580***	0.574***	1.775***	0.138***
	(0.0225)	(0.0379)	(0.003)	(0.0229)	(0.0407)	(0.014)
Head gender	0.417***	1.517***	0.0409***	0.226***	1.254***	0.055***
	(0.0982)	(0.149)	(0.008)	(0.0581)	(0.0729)	(0.025)
Head married	0.309*	1.362*	0.0308*	0.666***	1.947***	0.164***
	(0.159)	(0.217)	(0.014)	(0.100)	(0.195)	(0.009)
Flush toilet	-1.158***	0.314***	-0.1613***	-0.411***	0.663***	-0.096***
	(0.0471)	(0.0148)	(0.008)	(0.0406)	(0.0269)	(0.006)
Region (Rural=1)	0.873***	2.393***	0.0893***	0.0139	1.014	0.004
	(0.0540)	(0.129)	(0.005)	(0.0353)	(0.0358)	(0.013)
Sindh	-0.204***	0.815***	-0.0219***	-0.303***	0.739***	-0.073***
	(0.0695)	(0.0567)	(0.007)	(0.0535)	(0.0395)	(0.019)
KPK	0.703***	2.020***	0.0923***	-0.688***	0.503***	-0.169***
	(0.113)	(0.229)	(0.017)	(0.0794)	(0.0399)	(0.021)
Balochistan	-0.201*	0.818*	-0.0310*	-0.335***	0.715***	-0.082***
	(0.101)	(0.0824)	(0.010)	(0.0836)	(0.0598)	(0.023)
Constant	-6.547***	0.00143***		-2.525***	0.0801***	
	(0.505)	(0.000725)		(0.366)	(0.0293)	
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1						
We have estimated the impacts of shocks on poverty and food insecurity status of the households by using Binary Logit Model. Households' poverty status is a binary variable where 1 is assigned to the poor household, while 0 is assigned to non-poor. Likewise, binary variable of food insecurity is indicated that 1 is assigned if household is found having daily calorie intakes below 2350 calories per adult, 0 is assigned otherwise. Hence, the positive sign of shocks on both outcome variables will indicate the adverse effects of shocks on the poverty and food insecurity status. Odd ratios and marginal effects are also presented.						

Similar to the previously discussed effects of the rainfall shocks, again the influences of rainfall shocks are estimated as harmful impacts on poverty status, while beneficial impacts on food security. The negative sign is suggestive of the beneficial impacts. Table 3.8 makes it evident that average rainfall norm has negative sign for both poverty and food insecurity status of the households which demonstrates the likelihood of the beneficial influences, while rainfall shock demonstrates the harmful influences on the likelihood of being poor. And, rainfall shocks have beneficial impacts on food security. The adverse impacts of flood on food security, and beneficial impacts of rainfall shocks on food security indicates that if excessive rainfall occurs, which results in flooding will have adverse influences on food security. These results are again substantiating the previously discussed impacts of rainfall. Moreover, temperature shocks also have the similar sort of the findings as the case of rainfall (Table 3.8). Moreover, we have computed the marginal impacts which demonstrate that rainfall shocks cause increase in poverty and food insecurity by 2 percent and 4 percent respectively, while temperature shocks demonstrate stronger adverse impacts than rainfall. The results obtained from marginal effects for temperature indicates that it brings about increase in chances of poverty by 6 percent, while food insecurity by 10 percent respectively.

Moreover, we have estimated the separate models by using single shock variable in each model—separate for flood, rainfall, and temperature. The results are found more or less similar as we have described above (see appendix 3.8A & 3.8B).

3.6.3 Covariate Shocks and Inequalities in Expenditures, Income, and Calorie Intakes

We have discussed the impacts of covariate shocks on households' wellbeing in previous section. This section shows the estimated impacts of covariate shocks on expenditures, income, and food security with respect to their quantiles, which will weave up the impacts of shocks on inequalities in household expenditures, income, and calorie intakes. For empirical purpose, we have applied two approaches quantile regression, and Ordered Logit & Generalized Ordered Logit Model.

Table 3.9 demonstrates the estimated results from the application of quantile regression, where 25th quantile, 50th, and 75th quantiles have been used in order to see which quantile is being affected more. The overall impacts of covariate shocks such as flood, rainfall and temperature shocks are estimated similar as they have been discussed. However, to observe the magnitude of impacts with respect to quantiles we have applied the quantile regression. The estimated influences of the flood shocks are estimated again negative and statistically significant. However, the magnitude of these impacts varies from lower to higher quantiles. These negative impacts are much higher for lower quantiles which demonstrate the poor segment of the society while the higher quantiles are demonstrating the richer segment of the households. Table 3.9 indicates that coefficients are getting relatively smaller as we move towards the higher quantiles such as 25th, 50th, and 75th. Such negative and significant impacts are estimated for households' expenditures, income, and calorie intakes.

The impacts of climatic variables (rainfall and temperature) are also found negative and significant as we have discussed in the previous sections. Nonetheless, the magnitudes of these effects also vary quantile to quantile. The results demonstrate that the magnitude appears to be the smaller as we move to the higher quantiles. These impacts contain strong implications that poor and low quantile households are more severely affected by the covariate shocks as compared to the higher quantile households (Table 3.9)

Table-3.9: Quantile Regression Estimation for Impact of Flood and Climatic Shocks on Households' Well-being in Pakistan

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	q-0.25	q-0.50	q-0.75	q-0.25	q-0.50	q-0.75	q-0.25	q-0.50	q-0.75
	Log PAE expenditure			**Log PAE calorie intakes**			**Log monthly household income**		
Average flood	-0.265***	-0.205***	-0.205**	-0.349***	-0.302***	-0.219***	-1.007***	-0.969***	-0.756***
	(0.0754)	(0.0736)	(0.0955)	(0.0548)	(0.0480)	(0.0579)	(0.111)	(0.106)	(0.126)
Flood shock	-0.0135	-0.0166	-0.0184	-0.0119	-0.0168**	-0.0207**	-0.0952**	-0.0399**	-0.0175
	(0.0125)	(0.0122)	(0.0159)	(0.00909)	(0.00796)	(0.00961)	(0.0184)	(0.0176)	(0.0210)
Average rainfall	0.0116*	0.0368***	0.0467***	0.00312	0.00729*	0.0136***	0.0230**	0.0509***	0.0794***
	(0.00661)	(0.00644)	(0.00836)	(0.00480)	(0.00420)	(0.00507)	(0.00982)	(0.00939)	(0.0112)
Rainfall shock	-0.0338***	-0.0362***	-0.0348***	0.0378***	0.0310***	0.0248***	-0.0969***	-0.0871***	-0.0756***
	(0.00620)	(0.00605)	(0.00785)	(0.00450)	(0.00394)	(0.00476)	(0.00937)	(0.00896)	(0.0107)
Average temperature	-0.100***	-0.0978***	-0.105***	0.0838***	0.0627***	0.0443***	-0.182***	-0.164***	-0.142***
	(0.0129)	(0.0126)	(0.0163)	(0.00937)	(0.00821)	(0.00991)	(0.0192)	(0.0183)	(0.0218)
Temperature shock	-0.0927***	-0.0946***	-0.104***	0.0867***	0.0647***	0.0452***	-0.174***	-0.158***	-0.140***
	(0.0131)	(0.0127)	(0.0165)	(0.00948)	(0.00831)	(0.0100)	(0.0194)	(0.0185)	(0.0221)
Head agriculture	0.0791***	0.0312***	-0.0433***	0.0847***	0.0617***	0.0533***	0.190***	0.101***	0.0900***
	(0.0105)	(0.0102)	(0.0132)	(0.00759)	(0.00665)	(0.00803)	(0.0161)	(0.0154)	(0.0184)
Head self employed	0.0164	-0.00440	-0.0566***	0.0140*	0.00372	0.00222	0.374***	0.253***	0.202***
	(0.0107)	(0.0104)	(0.0136)	(0.00778)	(0.00681)	(0.00822)	(0.0165)	(0.0158)	(0.0188)
Head paid employee	-0.0747***	-0.113***	-0.166***	-0.0343***	-0.0401***	-0.0390***	0.274***	0.138***	0.0837***
	(0.00925)	(0.00902)	(0.0117)	(0.00671)	(0.00588)	(0.00710)	(0.0146)	(0.0140)	(0.0167)
Household size	-0.0511***	-0.0514***	-0.0501***	-0.0277***	-0.0293***	-0.0304***	0.0923***	0.0910***	0.0854***
	(0.000953)	(0.000929)	(0.00121)	(0.000691)	(0.000606)	(0.000731)	(0.00142)	(0.00136)	(0.00162)
Head age	0.00147***	0.00236***	0.00315***	0.00265***	0.00287***	0.00322***	0.00529***	0.00672***	0.00832***
	(0.000236)	(0.000230)	(0.000299)	(0.000171)	(0.000150)	(0.000181)	(0.000363)	(0.000347)	(0.000414)
Dependency ratio	-0.0913***	-0.0875***	-0.0950***	-0.0855***	-0.0806***	-0.0723***	-0.178***	-0.173***	-0.181***
	(0.00372)	(0.00363)	(0.00471)	(0.00270)	(0.00236)	(0.00285)	(0.00593)	(0.00567)	(0.00676)
Head gender	-0.0659***	-0.0750***	-0.0842***	-0.0426***	-0.0376***	-0.0477***	0.729***	0.458***	0.361***
	(0.0113)	(0.0110)	(0.0143)	(0.00820)	(0.00718)	(0.00867)	(0.0195)	(0.0187)	(0.0223)
Head married	-0.0838***	-0.0924***	-0.178***	-0.100***	-0.108***	-0.121***	0.0426	-0.0387	-0.101***
	(0.0197)	(0.0192)	(0.0249)	(0.0143)	(0.0125)	(0.0151)	(0.0299)	(0.0286)	(0.0341)
Flush toilet	0.183***	0.198***	0.224***	0.0430***	0.0438***	0.0531***	0.228***	0.251***	0.306***
	(0.00769)	(0.00750)	(0.00973)	(0.00558)	(0.00489)	(0.00590)	(0.0114)	(0.0109)	(0.0130)
Regional dummies	Yes	Yes	Yes	yes	yes	yes	Yes	yes	yes
Provincial dummies	Yes	Yes	Yes	yes	yes	yes	Yes	yes	yes
Constant	9.110***	9.177***	9.500***	7.848***	7.987***	8.115***	10.70***	11.28***	11.64***
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1									
Application of quantile regression, where 25th quantile, 50th, and 75th quantiles have been used in order to see what quantile is being affected more. The overall impacts of covariate shocks such as flood, rainfall, temperature, and inflation shocks are estimated similar as they have been discussed. However, the magnitude of these impacts varies from lower to higher quantiles. These negative impacts are much higher for lower quantiles which demonstrate the poor segment of the society, while the higher quantiles are demonstrating the richer segment of the households.									

(Alamgir, Furuya et al. 2021)have estimated the inequalities in the impacts of disasters on different income classes in Bangladesh. Our results match with the Alamgir, Furuya et al.2021. Apart from covariate shocks, households' socioeconomic elements are also used as the control variables which have significant influences on the well-being of households. Such elements include head gender, age, education, and employment status, while family size and dependency ratio also have the significant impacts on households' well-being (table-3.9). However, the magnitude of these control variables is going to be different as we move to the higher quantiles of the households' expenditures, income, and calorie intakes (Table 3.9).

3.6.4 Estimated Results from Generalized Ordered Logit Model

We have applied Ordered Logit (OL) model to estimate the impacts of covariate shocks on the likelihood of households to move on higher quantiles of expenditures, income, and calorie intakes respectively. The OL model is applied; because, we have five ordered categories from lower to the highest level.

Table 3.10 comprises the estimated results which is suggestive that flood and climatic variables have similar impacts, as we have discussed in previous discussions. In the context of Ordered Logit Model, the findings indicate that households are more likely to remain in the lower quantiles of expenditures, income, and calorie intakes due to the flood shocks. The coefficients have negative signs which determine the adverse effects of the flood shocks. Likewise, climatic variables have shown the adverse effects on income and expenditures which indicate that due to climatic shocks households are more likely to remain in lower quantiles of expenditures and income, while it has contrary impacts on calorie intakes. (Alamgir, Furuya et al. 2021) have estimated the inequalities in the impacts of disasters on different income classes in

Bangladesh. The lower quantile households are found the highly exposed to the disasters.

But we have applied Brant test on Ordered Logit Model to check the Parallel Regression assumption. The Brant test suggests that it appears statistically significant which will indicate the violation of the assumption. The estimated results suggest that the statistic of the test appeared to be the statistically significant which demonstrates that Ordered Logit is not appropriate in these models (Table 3.10). So, we have to move on the alternative option, Generalized Ordered Logit Model (GOLM).

Table 3.11 contains the estimated results of the covariate shocks and its impacts on expenditure, which will determine the magnitude of the effects, that may vary lower quantiles to the highest quantiles. The GOLM works like multinomial Logit model and we have used 5^{th} quantile as reference category. Moreover, we have reported Odd Ratio to interpret the coefficients of the variables. Such results demonstrate the impacts of climatic shocks on the inequalities in households per adult expenditures. The results are suggestive that flood shocks have adverse impacts on the inequalities in household expenditures. The negative sign indicates that other things remain constant; the increase of flood water is more likely to bring about increase in inequalities in household expenditures, which concludes that flood shocks are more likely to bring about inequality across different quantiles of expenditures (Table 3.11). Similarly, such impacts occurred for calorie intakes and income quantiles (see Table 3.11A & 3.11B in appendix).

Table 3.10: Impact of Shocks on Five Quantiles of Outcome Variables: Ordered Logit Model

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	OLM	Odd Ratio	OLM	Odd Ratio	OLM	Odd Ratio
	Expenditure quantiles		Income quantiles		Calorie intakes quantiles	
Average flood	-1.788***	-1.788***	-1.951***	-1.951***	-2.483***	-2.483***
	(0.333)	(0.333)	(0.326)	(0.326)	(0.328)	(0.328)
Flood shock	-0.108*	-0.108*	-0.140**	-0.140**	-0.151***	-0.151***
	(0.0582)	(0.0582)	(0.0609)	(0.0609)	(0.0451)	(0.0451)
Average rainfall	0.285***	0.285***	0.0635**	0.0635**	0.0757***	0.0757***
	(0.0284)	(0.0284)	(0.0293)	(0.0293)	(0.0274)	(0.0274)
Rainfall shock	-0.0652**	-0.0652**	-0.111***	-0.111***	0.205***	0.205***
	(0.0295)	(0.0295)	(0.0300)	(0.0300)	(0.0272)	(0.0272)
Average temperature	-0.304***	-0.304***	-0.393***	-0.393***	0.420***	0.420***
	(0.0565)	(0.0565)	(0.0546)	(0.0546)	(0.0547)	(0.0547)
Temperature shock	-0.326***	-0.326***	-0.382***	-0.382***	0.439***	0.439***
	(0.0572)	(0.0572)	(0.0552)	(0.0552)	(0.0552)	(0.0552)
Head agriculture	-0.326***	-0.326***	1.057***	1.057***	0.490***	0.490***
	(0.0481)	(0.0481)	(0.0539)	(0.0539)	(0.0442)	(0.0442)
Head self employed	0.235***	0.235***	1.574***	1.574***	0.0655	0.0655
	(0.0501)	(0.0501)	(0.0537)	(0.0537)	(0.0458)	(0.0458)
Head paid employee	-0.275***	-0.275***	1.163***	1.163***	-0.255***	-0.255***
	(0.0439)	(0.0439)	(0.0486)	(0.0486)	(0.0399)	(0.0399)
Household size	0.443***	0.443***	0.348***	0.348***	-0.218***	-0.218***
	(0.00587)	(0.00587)	(0.00588)	(0.00588)	(0.00509)	(0.00509)
Head age	0.0138***	0.0138***	0.0253***	0.0253***	0.0212***	0.0212***
	(0.00107)	(0.00107)	(0.00111)	(0.00111)	(0.00105)	(0.00105)
Dependency Ratio	-0.478***	-0.478***	-0.641***	-0.641***	-0.572***	-0.572***
	(0.0175)	(0.0175)	(0.0188)	(0.0188)	(0.0184)	(0.0184)
Head gender	-0.0847	-0.0847	1.821***	1.821***	-0.326***	-0.326***
	(0.0539)	(0.0539)	(0.0649)	(0.0649)	(0.0495)	(0.0495)
Head married	-0.132	-0.132	-0.0172	-0.0172	-0.789***	-0.789***
	(0.0936)	(0.0936)	(0.0919)	(0.0919)	(0.0824)	(0.0824)
Flush toilet	1.148***	1.148***	0.807***	0.807***	0.378***	0.378***
	(0.0329)	(0.0329)	(0.0322)	(0.0322)	(0.0317)	(0.0317)
Rural	-0.983***	-0.983***	-0.753***	-0.753***	0.0370	0.0370
	(0.0317)	(0.0317)	(0.0305)	(0.0305)	(0.0291)	(0.0291)
Sindh	0.391***	0.391***	-0.0353	-0.0353	0.338***	0.338***
	(0.0452)	(0.0452)	(0.0441)	(0.0441)	(0.0424)	(0.0424)
KPK	-0.726***	-0.726***	-0.840***	-0.840***	0.693***	0.693***
	(0.0713)	(0.0713)	(0.0732)	(0.0732)	(0.0646)	(0.0646)
Balochistan	0.301***	0.301***	-0.118*	-0.118*	0.360***	0.360***
	(0.0663)	(0.0663)	(0.0637)	(0.0637)	(0.0663)	(0.0663)
Brant Test (for Assumption of Parallel Regression)						
Chai^2 statistic	1160.05***		1780.87***		825.45***	
Conclusion	Not parallel		Not parallel		Not parallel	
The Brant test suggests that if it appears statistically significant which will indicate the violation of the assumption. The estimated results suggest that the statistic of the test is appeared to be statistically significant which demonstrates that Ordered Logit is not appropriate in these models So, we have to move on the alternative option, Generalized Ordered Logit Model (GOLM).						

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Moreover, the long run norm of average flood water has much stronger implication on both poverty and food insecurity of households. These findings also substantiate the previously discussed findings regarding flood events. The impacts of climatic shocks are suggestive of the adverse impacts on different quantiles of the expenditures. It is evident that the coefficients of the shock variables are declining as we move from the lowest to the highest quantiles which demonstrates that climatic shocks are causing increase in expenditure inequalities. Likewise, the impacts are estimated for household income and calorie intakes quantiles (see Table 3.11A & 3.11B in appendix). (Kleve, Davidson et al. 2017) have estimated the adverse impacts of disasters on different income classes of households, where the lower- and middle-income class households are more susceptible to the covariate shocks.

In a nutshell, covariate shocks are affecting the well-being of households, and furthermore, they are causing increase in inequalities in expenditures and households' income, and calorie intakes. The overall adverse impacts of shocks are having more strong influences on relatively lower quantiles of the aforesaid three well-being indicators. Specifically, flood shocks have more adverse impacts on inequalities across households.

Table 3.11: Generalized Ordered Logit Model for Five Quantile of Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reference	*GoLogit*	*Odds ratio*	*GoLogit*	*Odds ratio*	*GoLogit*	*Odds ratio*	*GoLogit*	*Odds ratio*
Fifth (highest)	**Lowest quantile (20)**		**Second quantile (40)**		**Third quantile (60)**		**Fourth quantile (80)**	
Average flood	-1.809***	0.164***	-2.182***	0.113***	-2.547***	0.0783***	-2.031***	0.131***
	(0.521)	(0.0854)	(0.440)	(0.0497)	(0.459)	(0.0359)	(0.588)	(0.0771)
Flood shock	-0.320***	0.726***	-0.166**	0.847**	-0.0110	0.989	-0.0605	0.941
	(0.0795)	(0.0577)	(0.0662)	(0.0561)	(0.0661)	(0.0654)	(0.0880)	(0.0828)
Average rainfall	0.191***	1.210***	0.325***	1.385***	0.295***	1.343***	0.355***	1.426***
	(0.0480)	(0.0581)	(0.0385)	(0.0533)	(0.0382)	(0.0513)	(0.0460)	(0.0655)
Rainfall shock	-0.122**	0.885**	-0.0941**	0.910**	-0.0987**	0.906***	-0.000787	0.999
	(0.0484)	(0.0428)	(0.0377)	(0.0343)	(0.0359)	(0.0325)	(0.0412)	(0.0412)

Average temperature	-0.327***	0.721***	-0.336***	0.715***	-0.262***	0.770***	-0.195**	0.823**
	(0.0869)	(0.0627)	(0.0745)	(0.0532)	(0.0772)	(0.0594)	(0.0975)	(0.0802)
Temperature shock	-0.328***	0.720***	-0.357***	0.699***	-0.285***	0.752***	-0.234**	0.791**
	(0.0881)	(0.0635)	(0.0752)	(0.0526)	(0.0776)	(0.0584)	(0.0978)	(0.0774)
Head agriculture	-0.0575	0.944	-0.323***	0.724***	-0.524***	0.592***	-0.604***	0.547***
	(0.0767)	(0.0724)	(0.0625)	(0.0452)	(0.0611)	(0.0362)	(0.0736)	(0.0402)
Head self-employed	0.413***	1.511***	0.319***	1.376***	0.170***	1.185***	0.0431	1.044
	(0.0867)	(0.131)	(0.0663)	(0.0912)	(0.0599)	(0.0710)	(0.0641)	(0.0669)
Head paid employee	-0.146**	0.864**	-0.248***	0.780***	-0.334***	0.716***	-0.413***	0.662***
	(0.0697)	(0.0602)	(0.0562)	(0.0438)	(0.0526)	(0.0377)	(0.0576)	(0.0381)
Household size	0.659***	1.932***	0.526***	1.693***	0.441***	1.554***	0.345***	1.412***
	(0.0120)	(0.0232)	(0.00875)	(0.0148)	(0.00747)	(0.0116)	(0.00723)	(0.0102)
Head age	0.00902***	1.009***	0.0137***	1.014***	0.0151**	1.015***	0.0173***	1.017***
	(0.00152)	(0.00154)	(0.00138)	(0.00139)	(0.00144)	(0.00146)	(0.00174)	(0.00177)
Dependency -cy ratio	-0.556***	0.574***	-0.522***	0.593***	-0.570***	0.565***	-0.552***	0.576***
	(0.0271)	(0.0155)	(0.0226)	(0.0134)	(0.0232)	(0.0131)	(0.0289)	(0.0167)
Head gender	-0.221***	0.802***	-0.166**	0.847**	-0.251***	0.778***	-0.159**	0.853**
	(0.0783)	(0.0628)	(0.0648)	(0.0549)	(0.0640)	(0.0498)	(0.0750)	(0.0640)
Head married	-0.0996	0.905	-0.203*	0.816*	-0.258**	0.772**	-0.312**	0.732**
	(0.120)	(0.109)	(0.108)	(0.0882)	(0.113)	(0.0870)	(0.139)	(0.102)
Flush toilet	1.256***	3.512***	1.246***	3.477***	1.238***	3.448***	1.355***	3.876***
	(0.0476)	(0.167)	(0.0457)	(0.159)	(0.0539)	(0.186)	(0.0820)	(0.318)
Rural region	-0.847***	0.429***	-0.951***	0.386***	-0.978***	0.376***	-0.969***	0.380***
	(0.0528)	(0.0226)	(0.0404)	(0.0156)	(0.0382)	(0.0144)	(0.0449)	(0.0170)
Sindh	0.395***	1.484***	0.608***	1.837***	0.493***	1.637***	0.255***	1.290***
	(0.0681)	(0.101)	(0.0598)	(0.110)	(0.0632)	(0.103)	(0.0806)	(0.104)
KPK	-0.584***	0.558***	-0.713***	0.490***	-0.749***	0.473***	-0.838***	0.433***
	(0.115)	(0.0641)	(0.0892)	(0.0437)	(0.0857)	(0.0405)	(0.100)	(0.0435)
Balochistan-an	0.485***	1.624***	0.641***	1.899***	0.446***	1.562***	0.130	1.139
	(0.114)	(0.185)	(0.0930)	(0.177)	(0.0932)	(0.146)	(0.116)	(0.132)
Constant	-8.142***	0.000291***	-8.986***	0.000125**	-9.082***	0.000114***	-11.08***	1.55e-05***
	(0.493)	(0.000144)	(0.404)	(5.06e-05)	(0.413)	(4.69e-05)	(0.516)	(7.99e-06)

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The GOLM works like Multinomial Logit Model and we have used 5th quantile as reference category. Moreover, we have reported Odd Ratio to interpret the coefficients of the variables. Such results demonstrate the impacts of climatic shocks on the inequalities in households per adult expenditures.

3.7 Conclusion and Policy Implication

This section deals with concluding remarks and policy implications of the ongoing study.

3.7.1 Concluding Remarks

Rising natural hazards in Pakistan makes it highly exposed to the risks of covariate shocks (climatic and flood). Specifically, the ultra-poor households are extremely vulnerable to these covariate shocks due to their constrained financial capacity. These shocks are projected to be harmful for households which have poor adaptive capacity. Therefore, before launching the policy agenda towards such people, it is imperative to quantify the sort of losses mainly these shocks are causing and what type of natural hazards are hurting more. So that a comprehensive and effective policy agenda may be designed to cushion the adverse influences of the occurring covariate shocks. Hence, the underlying study has objective to investigate the impacts of the covariate shocks on the well-being outcomes of the households in Pakistan. For empirical purpose, nationally representative HIES (2018-19) survey is used, while tehsil level climatic and flood related variables are merged with household dataset. Moreover, OLS, Binary Logit Model, and Generalized Ordered Models are applied to investigate the impacts of the shocks.

The OLS estimation suggests that flood shocks have severe adverse influences on households' wellbeing, such as log of per adult equivalent, log of monthly income, log of calorie intakes, and log of food and non-food expenditure share to the total expenditures. Moreover, climatic norms such as rainfall and temperature shocks have adverse impacts on the household's well-being, while rainfall has positive impacts on calorie intakes. The positive impacts on calorie intakes are due to higher agriculture productivity, whereas, the flood shocks have negative and significant effects on the calorie intakes. This implies that only rainfall has beneficial impacts on calorie intakes, but flood shocks have damaging impacts on food security due to excessive rainfall which cause flooding.

The application of Binary Logit Model is suggesting that flood and climatic shocks have adverse impacts on determining the poverty and food insecurity status of the households. However, in order to quantify the variations in the magnitude of the coefficients, Generalized Ordered Logit Model is applied on five ordered quantiles of the expenditures, monthly income, and calorie intakes by households. The estimated results suggest that the magnitude of the effects of the climatic variables varies across the quantiles. The results have established that covariate shocks are more hurting the lower quantiles as compared to the higher quantiles of the expenditures, income, and calorie intakes.

3.7.2 Limitations of the On-Going Research Essay

Every research has some limitations. So, the following are limitations of the on-going research.

i. We need to use the data of climatic factors from other sources to check the sensitivity and reliability of the impacts. We have approached the Pakistan Metrological Department (PMD) to take tehsil level data for rainfall and temperature norms. Nonetheless, the PMD does not have data of all tehsils, but have data for few stations, which does not fulfill the requirement of the study at significant level.

ii. We have to drop inflationary shock variable, as we have calculated prices from consumption module of the survey. To compute inflation, we have to calculate the rate of change of prices for which we need base year prices. Thus, due to limitation, impact of inflationary shock remained unexplored.

3.7.3 Policy Implications

The underlying study has estimated the adverse influences of the covariate shocks on households' well-being and are suggesting some policy implications. Specified recommendations on bases of obtained findings are outlined as follows:

- On the base of finding of our study, we may suggest that government should design social safety nets according to the climatic and environmental shocks. As BISP is one of the largest social protection programmes, it must be extended to the flood-prone disasters, and climatic-shocks.
- Specifically, policymakers must prioritize the lower quantile to enable them to cushion the adverse impacts of the climatic and flood-prone disasters.

Flood disaster appears to be the highly disastrous calamity; government must link the social safety nets with National Disaster Management Authority (NDMA), so that vulnerable households may be targeted earlier, and rescue them of being food insecure and chronic poverty.

CHAPTER 4

ESSAY 2: MEDIATING THE IMPACT OF ECONOMIC AND ENVIRONMENTAL VULNERABILITIES ON WELL-BEING THROUGH SOCIAL PROTECTION: EVIDENCE FROM DEVELOPING COUNTRIES

Abstract

The main objective of the underlying research work is to evaluate the mediating role of social protection expenditures on achieving well-being agenda against the economic and climatic shocks in developing countries. The study has employed three indicators of well-being: food insecurity, national level household expenditures, and accumulation of human asset. For empirical purpose, we used the unbalanced panel data of 94 developing countries. The selection of the countries is performed on the basis of availability of data (2001-2019) on economic and environmental vulnerabilities. For empirical purpose, the ongoing study applies the country fixed effect model. The estimated results suggest that social protection expenditures have the significant mediating role against the economic and environmental shocks in order to maintain the national level food security, increase in household expenditures, and increase in human asset accumulation in the developing countries. The study highlights that social protection expenditures have a much stronger mediating role against environmental shocks as compared to macro-economic vulnerabilities. These results have strong policy implications which can motivate the governments to increase their expenditures on social protection programs.

Key Words: Social Protection Expenditures, Economic and Environmental Shocks, Fixed Effect

4.1 Introduction

The main objective of the study is to unleash the mediating role of social protection expenditures against the covariate shocks such as economic and environmental shocks in developing countries. Primarily, the climatic and natural disaster-prone shocks intimidate the vulnerable segments of the developing countries (Catalano, Forni et al. 2020). A great number of the developing countries have limited institutional and financial resources to resist against climatic and environmental shocks (Center for Climate and Energy Solution, 2019; Climate Transparency, 2019). According to Global Climate Risk Index (2020), majority of the countries lying in top 10 of the most vulnerable countries to climatic and environmental shocks belong to the developing countries such as Dominica, Nepal, Thailand, Bangladesh, Vietnam, Pakistan, Philippines, Haiti, Myanmar, and Puerto Rico. These countries are included in low- and middle-income classification. From 1999 to 2018, twelve thousand plus natural disasters and climatic shocks engulfed 49,5000 human beings and $ 3.54 trillion across the world. These threats are projected to be increased over the time if the world does not respond them wisely and effectively (Eckstein, Künzel et al. 2019). Similarly, the macroeconomic shocks like inflation, recession, and productivity losses also have significant impacts on the lives of the households in the developing countries.

Existing literature suggests the adverse effects of climatic shocks on socioeconomic well-being, such as food insecurity, household expenditures, human health and nutrition. Moreover, the natural disasters also badly affect the infrastructures of health, education, and transportation ((Patel, Sharma et al. 2020); (Ahmad and Afzal 2021); (Firdaus, Senevi Gunaratne et al. 2019); (Asfaw, Carraro et al. 2017)). In the presence of such economic and environmental risks and vulnerabilities, the role of fiscal space to provide social protection gained immense significance. The international community, after the global recession of 2008, reaffirmed the provision of social protection to the most vulnerable segments of their societies. In such a manner, the developing countries also took initiative to protect their vulnerable segments, and they started to increase their budgetary expenditures for social protection programmes. The great majority of these countries launched different social protection programmes i.e., cash transfer programmes and other forms of the subsidies to protect the poor in order to cushion the adverse effects of the economic and climatic shocks (Ferraro and Simorangkir 2020).

There is no dearth of literature which has documented the beneficial role of social protection programmes in the developing countries. The literature shows that there are multiple forms of social protection programmes including cash transfer, in-kind, and Labour related programmes, along with social insurance. These programmes have increased the socioeconomic well-being of the people. As a result of these interventions, a great improvement has been witnessed in the areas of poverty reduction, adaptive capacity, food security, and Labour participation ((Handa, Seidenfeld et al. 2020); (Ferraro and Simorangkir 2020); (Bhalla, Handa et al. 2018)). Hence, these evidences show an encouraging role of social protection programmes in the developing countries. Thus, social protection programmes are the important instruments which enhance the adaptive capacity of the poor against the covariate shocks through provision of additional income in the form of cash transfers, health insurance, as well as the provision of other social assistances. (Asfaw, Carraro et al. 2017) also suggested the mediating role of social protection programmes against the climatic shocks in Zambia. The provision of social protection also increases the resilience power of the communities, and it enables them to resist against these climatic, and economic shocks (Mustafa, Ali et al. 2019).

It can be concluded that the role of government spending, in the form of social protection, is expected to be the most important instrument to tackle the adverse impacts of the covariate shocks, both at macro as well as micro levels in the developing countries. In spite of financial and institutional limitations, an expansion of fiscal space plays the mediating role against the prevailing shocks in order to maintain food security, household expenditures, and accumulation of human assets.

The underlying study, therefore, strives to estimate the mediating role of the social protection expenditures against both economic and environmental shocks. The estimated results predict that the social protection expenditures have positive, and significant mediating role against shocks.

4.1.1 Specified Objectives of Underlying Essay

The underlying essay aims to evaluate the mediating role of government expenditures on social protection against economic and environmental shocks in the developing countries. In fact, this study is an endeavor to establish a new perspective that the developing countries should definitely expand fiscal space for social protection programmes.

The specified objectives of this essay are outlined below:

1. To explore the mediating role of the fiscal/budgetary allocation for social protection on against the economic and environmental shocks on food insecurity.

2. To explore the mediating role of the fiscal/budgetary allocation for social protection against the economic and environmental shocks on human asset index.
3. To explore the mediating role of the fiscal/budgetary allocation for social protection against the economic and environmental shocks on national level household expenditures.

4.1.2 Significance of the Underlying Essay

The underlying study contributes in two ways. Firstly, it investigates the fiscal preferences of the governments in order to appease the adverse impacts of environment and economic vulnerabilities in the developing countries. Secondly, the study employs multiple outcome variables such as food insecurity, household expenditures, and human asset accumulation index. These variables have a potential to demonstrate social and economic aspects of well-being at national level. The study also establishes the mediating role of social protection programmes against covariate shocks. It motivates us to suggest the policy implication for increasing the budgetary allocation for social protection in the developing countries.

The subsequent parts of the underlying chapter comprise of section 4.2, which deals with the literature review, section 4.3 deals with the data description and methodological framework, section 4.4 deals with the results and discussion and section 4.5 deals with concluding remarks on the underlying chapter.

4.2 Literature Review

In developing countries, the available literature has documented the impacts of climate related natural disasters on different aspects of lives of the households, and such adverse impacts are documented at macro-level as well. There are long term and immediate impacts of the climatic disasters on health, food security, agriculture productivity, child stunted growth, and human capital formation (Ahmad, Mustafa et al. 2016); (Nellemann, Verma et al. 2011). So, we can discuss brief literature review of impacts of shocks on different aspects of well-being.

A huge strand of literature has discussed the adverse effects of the climatic and environmental shocks on agriculture productivity and food security. Such negative effects hold implication at both micro and macro level. As the study conducted by (Hoddinott and Kinsey 2000) has estimated the adverse influences of drought on the level of food security in Zimbabwe (Hoddinott 2006). There are some other studies which have estimated the impacts of climate-related shocks such as hurricane, rainfall, and flood have adverse impacts on determining the level of food security and hunger in developing countries (i.e., (Anderson, Bayer et al. 2020); (Islam and Kieu 2020); (Kogo, Kumar et al. 2021); (Van Epp and Garside 2019); (Asfaw, Carraro et al. 2017); (Ahmad, Mustafa et al. 2016); (Jungehülsing 2010); (Ahmad and Farooq 2010); (Angula 2010); (Serna 2011); (Gregory, Ingram et al. 2005)). Moreover, climatic and environmental shocks have significant adverse influences on health outcomes (Hayes and Poland 2018); (Paavola 2017); (Agwu and Okhimamhe 2009); (Mitchell, Tanner et al. 2007); (Reyes 2002). In a nutshell, climatic and environmental vulnerabilities have affected the well-being of the countries and households living in developing countries.

Like natural disaster and climatic shocks, economic shocks also impact the poverty and well-being of the households. Mainly, these shocks occur due to macroeconomic policy shifts. Recent literature suggests that macro-level economic vulnerabilities play important and significant role in determining the economic and household’s well-being in developing countries. As a study conducted by (Nabi, Shahid et al. 2020) have estimated the effects of vulnerabilities of economic growth, and inflation have significant influence on poverty-level in developing countries. Similarly, (Hossain and Mujeri 2020) have estimated the negative and significant effects of inflationary shocks on households' well-being in Bangladesh. (Sakyi, Bonuedi et al. 2018) have estimated the influence of impacts of trade related vulnerabilities on households' welfare in African countries. They have estimated that the adverse shocks in trade patterns have impacted the welfare of the people. Likewise, the evidences collected by other studies also indicate the impacts of macroeconomic policies on economies at both micro and macro levels in developing countries (Deyshappriya 2020); (Rustamovich 2019); (Lara Ibarra, Mendiratta et al. 2017).

After discussing the impacts of economic and environmental vulnerabilities on the well-being of households in developing countries, heaps of studies show the positive and significant role of social protection programs on the socioeconomic well-being of the households in developing countries ((Handa, Seidenfeld et al. 2020); (Ferraro and Simorangkir 2020); (Ambler and De Brauw 2019); (Mustafa, Ali et al. 2019); (Bhalla, Handa et al. 2018); (Kosec and Mo 2017)). Likewise, most recently the study conducted by (Cho, Avalos et al. 2021) has explored the impacts of social protection Programme and their budgetary allocations on mitigating the adverse impacts of Covid-19 in developing countries. Their study has explored the positive and significant influence of the social protection expenditures on the well-being of the communities and people living in developing countries. Similarly, (Asfaw, Carraro et al. 2017) have explored the positive and significant mediating role of the social protection Programme on the well-being of the households.

In sum, above discussed brief review of literature indicates the adverse impacts of economic and environmental vulnerabilities on the welfare of the households in developing countries. After that the role of cash transfer and other social protection

Programme is discussed in literature. The underlying study contributes in exploring the mediating role of the expansion in fiscal space regarding social protection programmes against both economic and environmental impacts on the hunger, households' expenditures, and accumulation of human assets in developing countries.

4.3 Conceptual Framework

Primarily, the underlying research essay has micro foundations of the framework of covariate shocks and its impacts on household well-being as provided by Asfaw et al., (2017), we have described in section 3.4 (see figure 3.1). We have established the channel of adverse impacts on impacting the food insecurity and poverty status of the households. In this section, we have extended micro-foundations to the macro-level and inclusion of the budgetary allocation on social protection by government to moderate the adverse influences of the macroeconomic and environmental shocks by following the framework provided by Brown et al., (2013).

Government spending on poverty reduction and building capacity of the households through various social safety nets is considered as the important policy agenda in developing countries. Figure 4.1 exhibits the conceptual framework which explains the linkages of the government spending on the social protection against shocks.

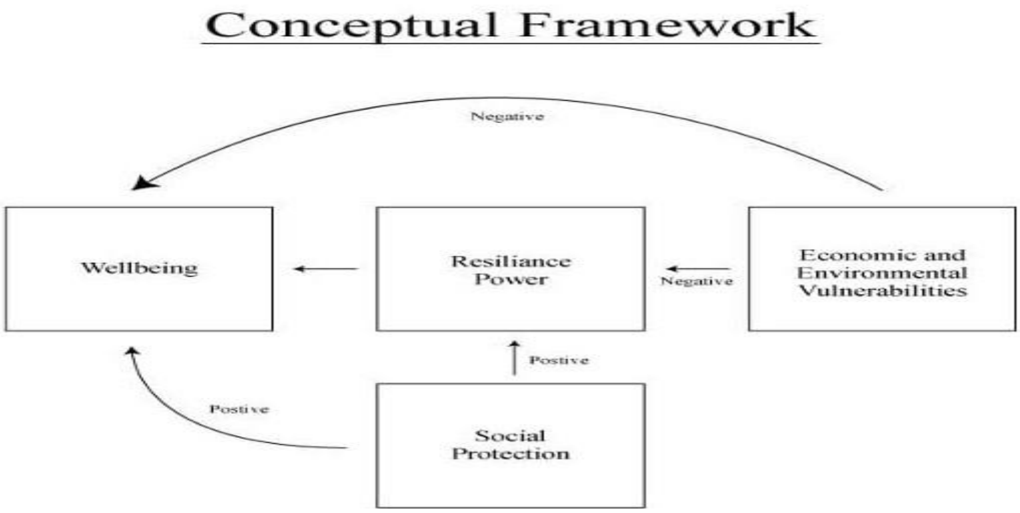


Figure 4.1: Conceptual Framework of mediating role of social protection (own construction)

Countries at macro-level faces multiple forms of shocks such as macroeconomic vulnerabilities and environmental shocks such as environmental degradation, climate change, floods, and other natural hazards etc., which bring about the problems like food insecurity, and declining quality of human development at macro-level (IPCC, 2015). In such scenario, the role of government is supposed to be significantly contributing in moderating the adverse impacts of covariate shocks. The available evidences from Latin American countries are showing the tremendous increase in government spending on the implementation of social safety nets to moderate the vulnerable segment of the societies, and it further influence the poverty reduction and economic prosperity at macro-level as well (Ocampo and Gómez-Arteaga, 2013). Moreover, existing literature suggests that increase in budgetary share on developmental expenditures such as on building infrastructure for health, education, and road expansions work effectively to raise the adaptive capacity of the people, and further the increase of government spending on social protection could increase economic growth and human well-being (e.g.; Fan, 2008; Tarnow, 2019; Ullah et al., 2021; Adeniyi, 2022).

4.4 Data Description and Methodological Framework

This section deals with data sources, measurement unit, variable description and methodological framework. For empirical purpose, data of 94 developing countries is taken from different sources. The country selection is made on the basis of availability of the data of expenditures on social protection, and economic and environmental vulnerability. But, the availability of data is not same period for each country. So, in panel setting, the data is unbalanced pooled data from 2001-2019. The total sample becomes 987 observations. The data of social protection expenditures to GDP is collected from International Labour Organization (ILO), while the data of economic and environmental vulnerability index (EVI) is taken from United Nations Committee for Development Policy Secretariat (UNCDPS), time series estimates for Least Developed Countries (LDC). The rest of the control variables are taken from World Development Indicators (WDI). The description of the variable is presented in Table-4.1.

Table 4.1: Description of the Variables

Variables	**Description of variables**	**Unit**
Dependent variables		
Household expenditure growth rate	National level growth rate of household expenditures	%
Human asset index	Index constructed on the basis of indicators: infant and maternal mortality, child stunted growth, literacy rate, and gender parity index by UNCDPS	Index
Prevalence of undernourishment (pou)	% of people who are undernourished	%
Independent variables		
Social protection expenditure to GDP	Share of social protection expenditure to GDP	%
Economic and environmental vulnerability index (EVI)	Index constructed on the basis of 8 indicators which determine economic and environmental vulnerability. It is constructed by UNCDPS.	Index
Economic vulnerability	It is measured by export instability index and one of components of EVI	Index
Climatic vulnerability	It is measured by index of victims and loss caused by climatic changes. It is also one of components of EVI	Index
People living in dry land index	% of people living in dry land area. It is also one of the components of EVI	Index
Control variables		
GDP per capita growth rate	GDP per capita growth rate	%
Inflation	National level inflation rate	%
Current account balance	Growth rate of current account balance	%
FDI inflow growth	Foreign direct investment growth rate	%

4.4.1 Variable Description

Economic and Environmental Vulnerability Index (EVI): This index is computed by United Nations Committee for Development Policy Secretariat for least developed countries. EVI is generated on the basis of 8 indicators which determine the economic and environmental vulnerability. Such indicators include export instability, export concentration, agriculture instability, share of agriculture, fishery, and forestry in

GDP (AFF), remoteness and lockedness, share of population living in costal and low elevated zones, population living in dry lands, and victims of disasters caused by environmental and climatic factors. The aforementioned indicators determine the composite index of economic and environmental vulnerability. Out of these mentioned variables, few (climatic factors etc.) are widely used as outcome variables by researchers from household survey data (Asfaw, Carraro et al. 2017); (Ahmad, Mustafa et al. 2016); but underlying study employs them for overall country-level analysis.

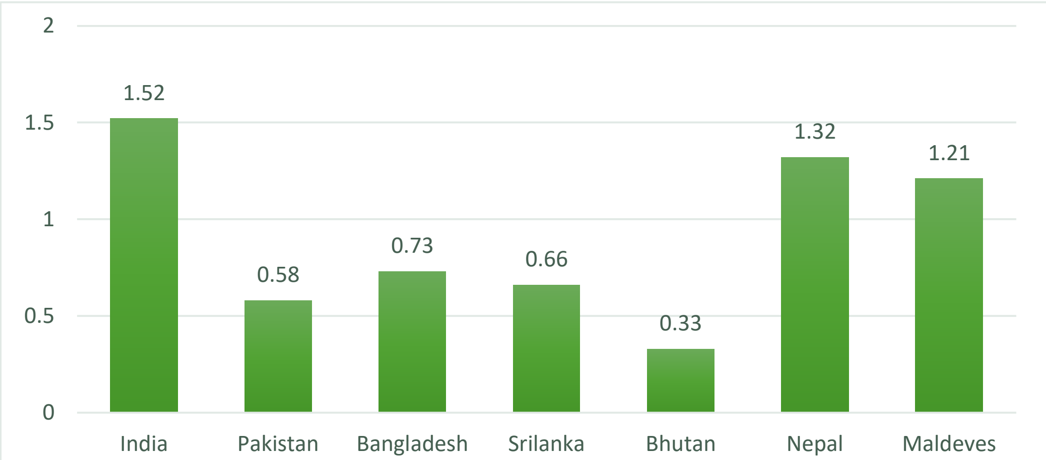
Human Asset Index (HAI): This index is also constructed by United Nations Committee for Development Policy Secretariat for least developed countries. To construct this index, 6 indicators are used: 1) child mortality rate, 2) maternal mortality rate, 3) prevalence of child stunting, 4) gross secondary school enrolment ratio, 5) adult literacy rate, and 6) gender parity index. This index indicates the quality of human asset. The higher value indicates the higher level of human asset in particular country. Indicators covered by HAI are used as outcome variables in available literature to see through the impacts of social protection programmes on socioeconomic development of households in developing countries (Mustafa, Ali et al. 2019); (Asfaw, Carraro et al. 2017).

Economic Vulnerability: Economic vulnerability is measured through export vulnerability, which is one of the prominent indicators of EVI. The index of export vulnerability is constructed by the UNCDPS. The underlying study has employed this indicator as the proxy of economic vulnerability in sampled countries.

Climatic Vulnerability: Climatic vulnerability is measured through the index constructed by the UNCDPS for environmental and climatic vulnerability. The index includes the victims and losses caused by the climatic and natural disasters. So, the ongoing study takes this index as the proxy of climatic and environmental vulnerability.

Social Protection Expenditures to GDP: This is also our main independent variable. Social protection expenditures are measured by percentage to GDP for each sampled country. Such expenditures include all sorts of expenditures.

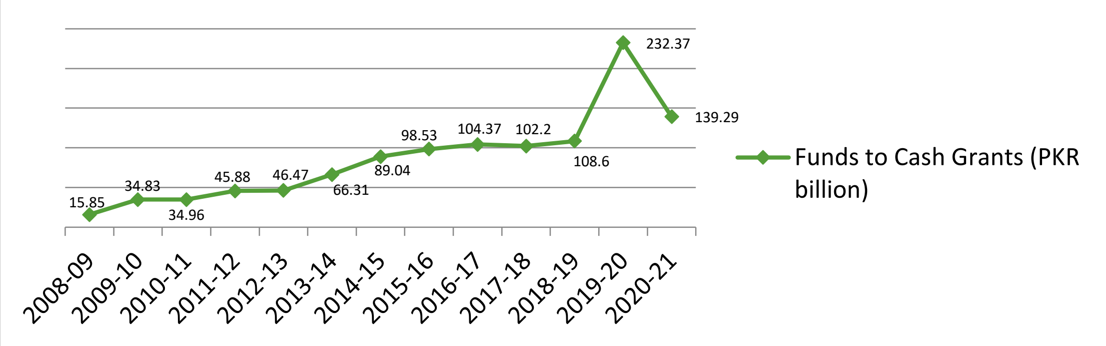
Figure 4.2: Annual Spending on Social Safety Nets in South Asia (% GDP)



Source: World Bank (2018)

For example, if we take the South Asian countries to see through the government spending differences on social protection. Figure 4.2 describes India, Nepal, and Maldives are placed among the top three positions among South Asian countries, while Pakistan stands at the second last bottom position. It evidently demonstrates that Pakistan is still behind the other South Asian countries. Nonetheless, if we look at Figure 4.3, Pakistan has increasing budgetary allocation on the implementation of cash transfer programmes over the years.

Figure 4.3: Pakistan’s Annual Budgetary Allocation on Cash Transfers



Source: Pakistan Economic Survey (2021-22)

Dependent Variables: Three dependent variables are employed to see through the mediating role of social protection expenditures against economic and environmental vulnerability. Such variables include national level household expenditures growth rate, prevalence of undernourishment which is indicator of severe food insecurity, and Human Assets Index (HAI). The description of these variables are presented in Table-4.1.

Control Variables: The ongoing study employs GDP per capita growth rate, inflation rate, current account balance, and growth rate of foreign direct investment (FDI) inflow. Per capita GDP growth rate determines the economic growth of the country or indicator of the living-standard of the people at national level, which is also supposed to hatch significant impacts on the outcome variables. Similarly, inflation is also controlled in the model, which is the indicator that directly influence the well-being of the people. Similarly, countries’ economic growth and development is mainly dependent on the level of investment in the country. So by controlling, all these mentioned control variables would help to see through impacts of factors other than environmental vulnerabilities. The data of these variables is taken from WDI. The description of these control variables is presented in Table 4.1, while the description of summary statistics of these variables is given in appendix (see Table 4.1A.)

4.4.2 Empirical Methodological Framework

As we have unbalanced pooled data setting of 94 countries, country fixed effect model has been applied to capture the unobservable heterogeneity across country. Usually, in panel data setting, two models are applied, fixed effect model, and random effect model. The choice between these two is seen through the application of Hausman specification test, that determines which model is more efficient and appropriate.

Hausman Null Hypothesis: Random Effect Model is appropriate.

Hausman Alternative Hypothesis: Fixed Effect Model is appropriate.

Hausman Null Hypothesis is rejected thus alternative hypothesis is accepted.

The results of Hausman test suggests that country fixed effect model will provide more efficient results as compared to random effect model. Moreover, theoretically, country fixed effect model is supported by a huge amount of literature (Halaskova and Bednář 2020); (Caminada, Goudswaard et al. 2012); (Caminada and Goudswaard 2005).

In country fixed effect model, it is assumed that the economic and environmental shocks influence the well-being of each country equally by fixing the country level's other heterogeneous factor, which brings about heterogeneity among the countries such as language, culture, and socio-political differences. Nonetheless, some factors are exclusively incorporated in the model as controlled variables, such as per capita GDP, inflation, foreign direct investment, and capital formation etc., which are given in following specifications of the fixed effect model.

The specification of the country fixed effect model is given as follows:

$$logY_{i,t} = \beta_i + \alpha_1 logSP_{i,t} + \gamma_i VI_{i,t} + \beta_i X_{i,t} + \mu_{i,t} \quad \text{………} \quad (4.1)$$

In equation (4.1), $logY_{i,t}$ represents the three outcome variables for country i and time t: a) log of household expenditure growth rate, b) log of human asset, and c) log of prevalence of undernourishment. These dependent variables are assumed to be changed within a country with the passage of time. Moreover, the aggregate household expenditures are taken as aggregate level without disaggregation of the expenditures by quintiles. Log of SP indicates the log of social protection expenditures to GDP for country i and time t, while $VI_{i,t}$ indicates the indices of economic and environmental vulnerability as discussed in Table 1. Moreover, $X_{i,t}$ represents the vector of control variables. The equation (4.1) specifies the impacts of social protection Programme in the presence of economic and environmental shocks.

Hence, in order to estimate mediating role of social protection programmes against economic and environmental indices, we need to introduce the interaction term of social protection expenditures with each index of economic and environmental indices separately. So, the equation (4.1) will have additional independent variables of interaction term, which is given as follows:

$$logY_{i,t} = \beta_i + \alpha_1 logSP_{i,t} + \gamma_i VI_{i,t} + +\eta_i logSP_{i,t} * VI_{i,t} + \beta_i X_{i,t} + \mu_{i,t} \quad \text{……….}(4.2)$$

In equation (4.2), rest of the settings are same as described in equation (4.1). However, the inclusion of interaction term captures the mediating role of the social protection expenditures against the economic and environmental indices, such as economic vulnerability, and climatic vulnerability, and composite index of both economic and environmental vulnerability. The parameter η_i will determine the empirically estimated estimate of the mediating role. If empirically estimated results indicate that η_i>0, then it will demonstrate the mediating role of social protection expenditures for human asset and growth rate of household expenditures, while for prevalence of undernourishment, η_i<0 will demonstrate the mediating role of the social protection expenditures against the economic and environmental vulnerability indices.

Apprehension of endogeneity in above specified models seems not serious due to reasons given as follows: i) since the covariate shocks are exogenous in nature, which demonstrates that there is no threat of the presence of the endogeneity in the model, and ii) the country-specific fixed effect model covers the country level heterogeneity or differences, the chances of differences in outcome variables in the model due to country-specific differences is not likely to happen. So, the all specifications of the models we have implemented are threatened by the problem of heterogeneity.

4.5 Results and Discussion

This section weaves up the estimated impacts of mediating role of the public expenditures on social protection programmes against economic and environmental expenditures in developing countries. For empirical purpose, we have applied country fixed effect model to estimate the impacts of social protection programmes on macro-level of food insecurity, household expenditures, and human asset index. We have discussed the mediating role of expenditures on social protection on each outcome variable as follows:

Table 4.2 comprises the estimated results for prevalence of undernourishment (PoU), which is proxy of food insecurity in country. Moreover, it is indicator of the food poverty as well. Where two models are estimated by fixed effect approach, our primary focus will be on the estimated results from country fixed effect, because it controls the country specific unobservable factors and it is justified by Hausman specification test.

The results suggest that index of the victims of climatic shocks is having the positive and significant impacts on the log of prevalence of undernourishment, which demonstrates the adverse effects of the climatic vulnerability on the food security of developing countries. The positive sign implies that other things remain same, with the increase of climatic vulnerability; there will be increase in prevalence of undernourishment by 7% in developing countries. Likewise, the results remain consistent, if we introduce time dummies in the models. Such evidence demonstrates the harmful influences of the vulnerability to climate change on the food security in developing countries. Similarly, the positive and significant influences of the economic instability on prevalence of undernourishment are estimated, which again highlights the adverse effects on determining the food security of the countries. If we observe closely, climatic vulnerability has much higher adverse effects on the level of food security as compared to economic vulnerability.

The interaction term of social protection expenditures with economic instability shows the negative sign which demonstrates that other things remain same; when both economic instability and social protection expenditures are interacted, the adverse impacts are deteriorated. Although insignificant interaction becomes insignificant, but makes significant adverse impacts of economic instability lesser, which indicates that social protection expenditures mediate the adverse effects of economic instability. However, we may say it weak mediating role of social expenditures against the economic instability. Moreover, the interaction term of social protection expenditures and climatic vulnerability has negative and statistically significant influences on prevalence of food insecurity, which demonstrates the strong mediating role of the social protection expenditures on food insecurity against climatic vulnerability.

Table 4.2: Social Protection Expenditure, Economic and Environmental Vulnerability and food Insecurity

Log of PoU	(1) Fixed Effects	(2) Fixed Effects
Log social protection spending	0.0562	0.0623
	(0.0547)	(0.0562)
Climatic vulnerability (CV)	0.0742**	0.0719**
	(0.0379)	(0.0326)
Economic instability (EI)	0.00394	0.00448**
	(0.00290)	(0.00218)
People living in dry land index	-0.0143***	-0.0122***
	(0.00387)	(0.00396)
Interact dry*social protection	5.83e-05	7.41e-05
	(0.000179)	(0.000181)
Interact EI*social protection	-0.000272	-0.000282
	(0.000322)	(0.000325)
Interact CV*social protection	-0.0218**	-0.0206**
	(0.00948)	(0.00803)
Dependency ratio	0.0147***	0.0144***
	(0.00393)	(0.00383)
Current account	-0.000607	-0.000755
	(0.00107)	(0.00112)
FDI inflow	0.000197	-0.000499
	(0.00202)	(0.00212)
GDP growth per capita	0.00246	0.00293
	(0.00329)	(0.00333)
Inflation	0.00221**	0.00226**
	(0.000917)	(0.000924)
Constant	1.722***	1.718***
	(0.315)	(0.309)
Observations	987	987
R-squared	0.351	0.358
Number of countries	94	94
Country FE	YES	YES
Year dummy		YES
We have applied country fixed effect model to estimate the impacts of social protection programmes on macro-level of food insecurity (POU). The results suggest that index of the victims of climatic shocks has the positive and significant impacts on the log of prevalence of undernourishment which demonstrates the adverse effects of the climatic vulnerability on the food security of developing countries. The interaction term of social protection expenditures and climatic vulnerability has negative and statistically significant influences on prevalence of food insecurity, which demonstrates the strong mediating role of the social protection expenditures on food insecurity against climatic vulnerability.		

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

The estimated results for mediating role against climatic vulnerability imply that the increase of expenditures on social protection programmes mediate the adverse influences of the climatic vulnerability on food insecurity by 2%. In other words, social protection expenditures help developing countries to appease the adverse impacts of climatic vulnerability on food security by 2%.

The third indicator of the environmental vulnerability is people living in dry land. The estimated results for such index are indicative of not having adverse impacts on the determination of the food insecurity in country. And the interactions of the variable with social protection expenditures do not hold any mediating role. These results indicate that social protection expenditures have much stronger and significant mediating impacts against climatic vulnerability as compared to the economic instability in developing countries. Our results are in line with past evidences i.e. (Handa, Seidenfeld et al. 2020); (Ferraro and Simorangkir 2020).

After food insecurity, household well-being is estimated through the index of human assets. Such human asset includes infant mortality rate, maternal mortality rate, child stunted growth, enrollment in secondary schools, and gender parity. Human asset index is constructed on the basis of these mentioned indicators.

Table 4.3 encompasses the estimated impacts for mediating role of the expenditures on social protection against economic and climatic vulnerabilities on human asset index. The estimated results are indicative of the negative and significant impacts of the economic vulnerability on the human asset, while climatic vulnerability does not have any significant effects on human asset index in developing countries.

Table 4.3: Social Protection Expenditures, Economic and Environmental Shocks, and Human Asset Index

Human asset index	(1)	(2)
	Fixed Effects	Fixed Effects
Log social protection expenditure (SP)	0.722	0.883
	(0.875)	(0.920)
Climatic vulnerability (CV)	-0.265	-0.307
	(0.412)	(0.412)
Economic Vulnerability (ES)	-0.0861*	-0.0832*
	(0.0464)	(0.0492)
Interact ES*SP	0.00754*	0.00724*
	(0.00430)	(0.00455)
Interact CV*SP	0.147	0.169
	(0.162)	(0.162)
Dependency ratio	0.0106	0.0111
	(0.0358)	(0.0362)
Current account	0.0242**	0.0260**
	(0.0109)	(0.0112)
FDI inflow	-0.00112	-0.00251
	(0.0298)	(0.0305)
GDP growth per capita	0.0811**	0.0792*
	(0.0385)	(0.0427)
Inflation	0.0212***	0.0204***
	(0.00751)	(0.00770)
Constant	67.69***	68.32***
	(2.768)	(2.779)
Observations	987	987
R-squared	0.320	0.331
Number of countries	94	94
Country FE	YES	YES
Year dummy		YES
Through fixed effect model we have estimated impacts for mediating role of the expenditures on social protection against economic and climatic vulnerabilities on human asset index. The estimated results are indicative of the negative and significant impacts of the economic vulnerability on the human asset, while climatic vulnerability does not have any significant effects on human asset index in developing countries. The interaction term shows the positive and significant impacts on human asset index against the economic shocks. The positive and significant impacts suggest the mediating role of the social protection expenditures against the economic vulnerability in order to maintain human asset quality.		

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

The interaction term shows the positive and significant impacts on human asset index against the economic shocks. The positive and significant impacts are suggestive of the mediating role of the social protection expenditures against the economic vulnerability in order to maintain human asset quality. However, it does not show any mediating role against the climatic vulnerability in the case of human asset (Table 4.3).

Table 4.4: Social Protection Expenditures, Economic and Environmental Shocks, and Human Asset Index

Human Asset Index	(1)	(2)
	Fixed Effects	Fixed Effects
Log social protection expenditure (sp)	-0.748	-0.543
	(1.165)	(1.173)
Economic and environmental vulnerability index (evi)	-0.753***	-0.765***
	(0.218)	(0.215)
Interact sp*evi	0.0154*	0.0154*
	(0.00868)	(0.00848)
Dependency ratio	0.0147	0.0138
	(0.0334)	(0.0334)
Current account	0.0346**	0.0363**
	(0.0147)	(0.0153)
FDI inflow	-0.0300	-0.0304
	(0.0348)	(0.0353)
GDP growth per capita	0.0913**	0.0909**
	(0.0394)	(0.0435)
Inflation	0.0142**	0.0134**
	(0.00641)	(0.00643)
Constant	92.89***	94.14***
	(7.633)	(7.481)
Observations	987	987
R-squared	0.311	0.313
Number of countries	94	94
Country FE	YES	YES
Year dummy		YES
In this model when we use a composite index of economic and environmental vulnerability (EVI), a strong mediating role of social protection is estimated. Increase in social protection expenditures help the countries to mediate the adverse effects of the adverse impacts of composite index of economic and environmental vulnerabilities on maintaining human asset by 1% to 2% in developing countries.		

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

But, when we use a composite index of economic and environmental vulnerability (EVI), a strong mediating role of social protection is estimated. Table 4.4 comprises the estimated impacts of such model. The results imply that the increase in social protection expenditures help the countries to mediate the adverse effects of the adverse impacts of composite index of economic and environmental vulnerabilities on maintaining human asset by 1% to 2% in developing countries. Our findings are similar with recent past empirical findings i.e. (Ambler and De Brauw 2019); (Mustafa, Ali et al. 2019).

Brambor et al. (2006) suggests that it is incorrect to decide on the inclusion of interactive terms simply by looking at the significance of the coefficient of interactive terms. The marginal effect should be observed by constructing confidence intervals for the estimates of social protection and interactive term. If the interval lies above the zero line, then the effect is significantly positive and vice versa.

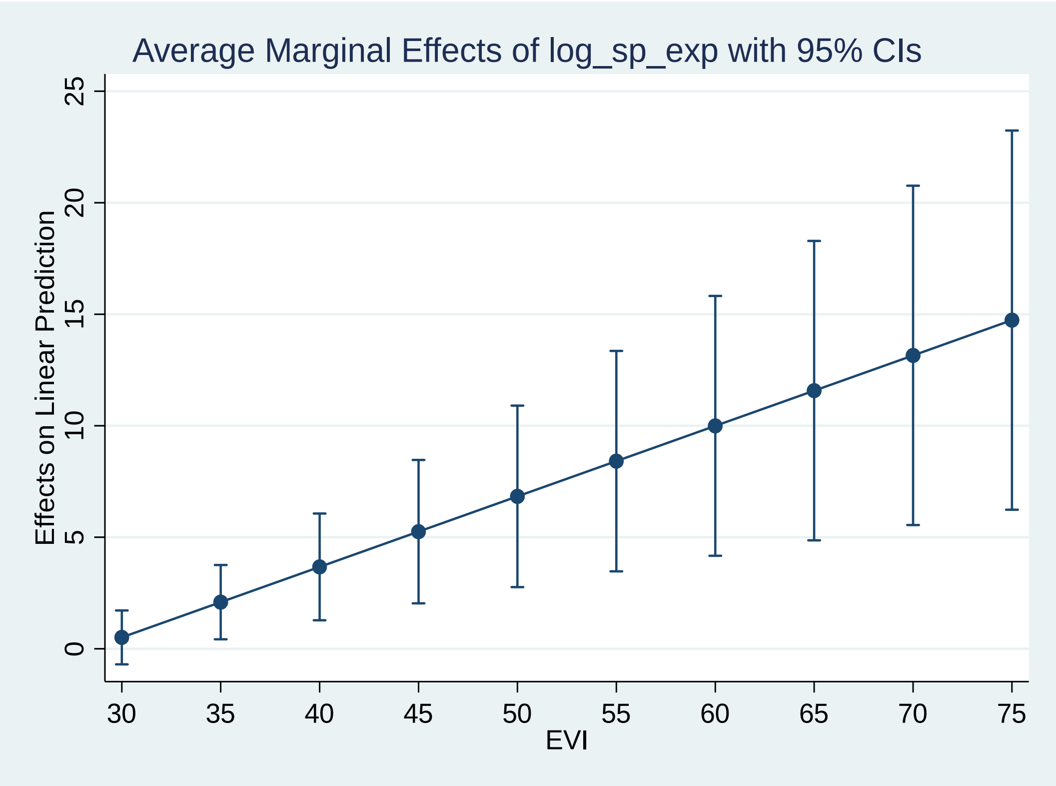


Figure 4.4 Determining the Range of Significance of the Marginal Effect of sp*EVI

In our model interaction term of social protection, environmental index is used to check the mediating role of social protection. Brambor et al. (2006), says if the interval lies above the zero line, then the effect is significantly positive and vice versa.

Finally, the study attempts to explore the impacts of economic and climatic vulnerability on household expenditures and mediating role of the social protection expenditures on household expenditures against such shocks or vulnerabilities.

Table-4.5: Social Protection, Economic and Environmental Shocks, and Household Expenditure Growth

Log of household expenditure growth	(1) Fixed Effects	(2) Fixed Effects
Log of social protection spending	0.292***	0.318***
	(0.0852)	(0.0902)
Climatic Vulnerability (CV)	-0.230***	-0.242***
	(0.0653)	(0.0639)
Economic instability (EI)	0.00524	0.00579
	(0.00369)	(0.00382)
Dry land	0.0234	0.0230
	(0.0147)	(0.0147)
Interact dry*social protection	-0.000592**	-0.000576**
	(0.000228)	(0.000228)
Interact EI*social protection	0.000748*	0.000834**
	(0.000394)	(0.000401)
Interact CV*social protection	0.0709***	0.0736***
	(0.0197)	(0.0184)
Dependency ratio	0.00251	0.00216
	(0.00476)	(0.00486)
Current account	-0.00241*	-0.00243*
	(0.00127)	(0.00130)
FDI inflow	-0.00253	-0.00315
	(0.00798)	(0.00800)
GDP growth per capita	0.0247***	0.0247***
	(0.00853)	(0.00867)
Inflation	-0.000249	-8.20e-05
	(0.000639)	(0.000697)
Constant	-0.225	-0.0671
	(0.611)	(0.611)
Observations	987	987
R-squared	0.390	0.410
Number of c_id	94	94
Country FE	YES	YES
Year FE		YES
In this model we attempt to explore the impacts of economic and climatic vulnerability on household expenditures and mediating role of the social protection expenditures on household expenditures against such shocks or vulnerabilities.		

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

Table 4.5 comprises the estimated results for household expenditures. Estimated results indicate that log of social protection expenditures is statistically significant and positive on household expenditures in developing countries. It is evident that one percent increase in social protection expenditures to GDP causes increase in household expenditure growth by 2% to 3%, which is very beneficial for the economic growth of those countries who are mainly dependent on household expenditure like Pakistan.

Furthermore, results suggest that climatic vulnerability has negative and significant impacts on the household expenditure growth. But, the interaction of the social protection expenditures suggests the positive and significant effects, which implies that social protection expenditures mediate the adverse effects of the climatic vulnerability (Table 4.5). Likewise, the social protection expenditures do have significant and mediating role against the economic vulnerability in developing countries. Again, the findings imply that social protection expenditures show much stronger mediating impacts against the climatic vulnerabilities, as compared to the economic impacts. . Recent empirical studies Asfaw, Carraro et al. 2017), (Bhalla, Handa et al. 2018) and (Kosec and Mo 2017) also support our findings.

Apart from social protection, and economic and environmental vulnerabilities, we have used dependency ratio, current account balance, FDI, GDP growth rate, and inflation rate as control variables in above discussed models. The estimated results demonstrate that dependency ratio, inflation, GDP growth rate, and current account balance are the other factors that have significant impacts on previously discussed outcome variables. But, the impacts of such control variables vary from variable to variable.

4.5.1 Placebo Checks Using Leads

In order to check the quality of specifications, we have estimated the placebo checks using leads—future environmental shocks and social protection expenditures should not have significant impacts on present outcomes. For that purpose, we have generated the leads on log of social protection expenditures, environmental shocks, and interaction in terms of both social protection and environmental shocks. And, outcome variables for present time, such as food insecurity, human asset index, and growth in household expenditures are regressed on future (leads) of the shocks and expenditures on social protection. Table 4.6 demonstrates that future environmental shocks and social protection expenditures are not found showing the significant impacts on present outcomes at country level.

Table 4.6: Placebo Checks by Using Leads: Social Protection and Environmental Shocks

	Outcome Variables in Present Time		
Variables	HAI (Present)	POU (Present)	HEC Growth (Present)
Future Variables			
Log of social protection expenditure (SPE) Future	0.0715	0.0690	0.165
	(1.136)	(0.617)	(0.149)
Environmental shock (EVI) future	0.0804	-0.0520	0.0105
	(0.0635)	(0.0363)	(0.00697)
Interaction SPE with EVI future	-0.000490	-0.00355	-0.00145
	(0.00511)	(0.00395)	(0.00107)
Dependency ratio (Present)	0.00237	0.161***	-0.000448
	(0.0358)	(0.0431)	(0.00507)
Current account (Present)	0.0318**	-0.000816	-0.00216*
	(0.0125)	(0.00742)	(0.00125)
FDI inflow (Present)	-0.00904	-0.0136	-0.00104
	(0.0296)	(0.0341)	(0.00836)
GDP growth (Present)	0.0784*	0.0582	0.0227***
	(0.0411)	(0.0571)	(0.00791)
Inflation (Present)	0.0164**	0.0130	0.000206
	(0.00686)	(0.00816)	(0.000659)
Constant	66.82***	5.302*	0.624
	(3.247)	(2.994)	(0.438)
Observations	986	986	986
R-squared	0.009	0.063	0.023
Number of c_id	94	94	94
Placebo Results: social protection and environmental shocks with leads/future are found statistically insignificant which indicates that future shocks and social protection expenditures do not have impact on outcomes of today.			

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

4.6 Concluding Remarks

Economic and environmental vulnerabilities threaten the maintaining well-being agenda in developing countries. The majority of developing countries have limited financial and institutional resources to cope with such vulnerabilities. According to Global Climate Risk Index (2020), majority of countries that lie in top 10 list, among them the most vulnerable countries to climate and environmental shocks belong to the developing countries. And, these highly vulnerable countries are from the cohort of low and middle income. The climatic and natural disaster-prone shocks hurt the economies at both macro and micro-levels. In the face of such adverse shocks, role of social protection expenditures is rising, and the encouraging impacts of social protection programmes have motivated the governments to increase the budgetary share of the social protection programmes in developing countries. Such fiscal space performs by believing in the mediating role of these expenditures against the economic and environmental vulnerabilities to cushion its adverse influences.

Therefore, the underlying dissertation aims at exploring the mediating role of the budgetary share of social protection programmes against the economic and environmental vulnerabilities in developing countries. For empirical purpose, we have used the unbalanced panel data of 94 developing countries. The selection of the countries is performed on the basis of availability of data on economic and environmental vulnerability. The data is collected from WDI and United Nations Committee for Development Policy Secretariat (UNCDPS), time series estimates for Least Developed Countries (LDC). In order to estimate the impacts, we have applied the country fixed effect model.

We have employed three outcome variables such as food insecurity, household expenditures, and human asset accumulation at country level. Human asset accumulation comprises the enrolment, gender parity, child stunted growth, maternal mortality, and child infant mortality. The estimated results suggest that social protection expenditures have the significant mediating role against the economic and environmental shocks in order to maintain the national level food security, and increase in household expenditures, and increase in human asset accumulation in developing countries. The study highlights that social protection expenditures have much stronger mediating role against environmental shocks as compared to only macro-economic vulnerabilities. These results have strong policy implication which motivates the governments to increase the expenditures on social protection programmes.

CHAPTER 5

ESSAY 3: TARGETING PERFORMANCE: PROPOSAL FOR SHOCK ADJUSTED TARGETING METHOD

Abstract

Pakistan being the highly vulnerable country to the economic and environmental shocks, the role of BISP cash transfer becomes highly important. The current targeting method of the BISP is highly depending on the formulation of PMT score (which is static in nature), and it is not capturing covariate shocks. So, third essay maintains focus on the shock adjusted PMT score. Primarily, analysis is based on Household Integrated Expenditure Survey (HIES) 2018-19, which a nationally representative household survey, and conducted by the Pakistan Bureau of Statistics. The sample we have is 24,809 households from four provinces of Pakistan (Punjab, KPK, Sindh, and Balochistan). From HIES, we have estimated the PMT score without shocks, while other socioeconomic profile of households is measured from this household survey. The data of tehsil level flood water covering area square kilometer is collected from NASA MODIS Satellite data, whereas, tehsil level climatic data of rainfall and temperature is taken from European Center for Medium-Range Weather Forecasts (ECMWF). In order to merge it with tehsil's information, we have obtained the code classification of tehsils available in HIES. After identification of tehsils from HIES household survey data, we merged all flood and climatic variables by using tehsil codes as key identifier. Then we estimated shock adjusted PMT score after merging covariate shocks data with HIES data. Overall targeting performance of shock adjusted model is increased to 67 percent as compared to 60 percent targeting performance of without shock model. Coverage of bottom 20 percent from urban areas is decreased to 42 percent as compared to 55 percent previously. Urban areas were given over coverage in previous model adopted by BISP, based on HIES 2013-14. This motivates us to suggest policymakers to adopt shock adjusted targeting method which is not only dynamic itself but also captures dynamic nature of poverty.

Keywords: Targeting Performance, Proxy Means Test, Targeting Efficiency

5.1 Introduction

In this era of globalized world, life is fraught with multifaceted mix of opportunities and risks. As World Development Report 2014 narrates that financial crisis, fuel and food created disturbances to world economy as a whole. In Sub Saharan African and Asian countries (South Asia particularly), many segments of society are poor and many sections are vulnerable to adverse economic shocks. World development agencies, policymakers and national governments struggle to identify the poor and vulnerable sections of the society to target them. Targeting strategies identify two groups of society. First group consists of those people who are suffering chronic poverty or those who could not meet their food expenditure and fall below the poverty line. They need long term assistance. Second group consists of those people who are on or slightly above the poverty line. This group is highly vulnerable to negative economic and climatic shocks and there is high probability to fall below the poverty line. They can face food insecurity and, thus they need short-term assistance.

Different targeting methods are used around the world to identify the poor and vulnerable groups of society. Exclusion and inclusion are two important targeting errors. Exclusion error occurs when eligible poor people are not selected and excluded from the safety Programme. Inclusion error occurs when the non-poor is selected by targeting method and included in the Programme. Common targeting methods are community-based targeting, geographic targeting, self-targeting, means tests and proxy means tests. In community-based targeting, groups of community leaders and members determine household eligibility but this method is vulnerable to elite capture and eligibility decisions can lack transparency. In geographic targeting, targets are set by location, including all residents within a location. It is easy to implement and transparent and it can rapidly target in response to natural disasters and other large covariate shocks. But it does not account for differences in household well-being in the area. In self-targeting, benefits and transaction, costs are set so that only needy households enroll. Stigma and lack of Programme knowledge may discourage participation. In means test, actual consumption or income is compared to eligibility threshold. Means tests are very accurate with good income or consumption data. But it is expensive to collect income or consumption data for all potential beneficiaries. In proxy means test, consumption is measured through proxies, which are readily observable and verifiable variables and it is compared to eligibility threshold. Internationally proxy means test is used in different social safety nets as a tool to target the poor households.

5.1.1 Background of BISP

In July 2008, Benazir Income Support Programme was initiated as a main social safety net in Pakistan. BISP provided PKR 1,000 as an unconditional cash transfer to ever married women (Gazdar 2011). At the time of launch of BISP, senators and members of national assembly were given responsibility to nominate the eligible households from their constituencies (Khan and Qutub 2010). Eight thousand application forms were given to each member of legislative assembly to enlist deprived and unprivileged residents of their area. Their data was verified from NADRA. Initially, the eligibility filters were: beneficiary income should not be more than PKR 6,000 per month, land owned should not be more than three acres, oversees Pakistani card or passport, beneficiary or any member of household should not be the government employee or should not have any bank account (Farooq 2014), (Haseeb and Vyborny 2016).

As evident selection criterion was at the discretion of the parliamentarians. Thus, a great number of beneficiaries qualified for the said Programme. (Farooq 2014) used independent survey data named Pakistan Panel Household Survey 2010 done by Pakistan Institute of Development Economics and found that more than 16 percent of beneficiaries of the Programme were not eligible for BISP. Donor agencies, World Bank (2013) and research scholars raised hue and cry about the long-term sustainability of social safety net. Due to criticism from opposition and donor agencies about the transparency of Programme, government with the help of technical assistance of World Bank established National Social Economic Registry (NSER). NSER maintains the 27 million households' registry of social economic characteristics, which was used to construct poverty scorecard through Proxy Means Test (Saeed and Hayat 2020). Henceforth, BISP is using PMT as the targeting tool to determine eligibility criteria. According to economic survey 2011-12 PMT shows the welfare of households from 0 to 100. A household with the score of 16.17 or below is eligible and household whose score is above this cutoff point is not eligible for this Programme (Cheema, Farhat et al. 2014). Through PMT poverty scorecard, 7.7 million households were filtered as eligible for BISP. Currently, BISP, by using NSER data and PMT targeting method, is providing cash transfer of PKR 1,500 per month to 5.57 million households.

5.1.2 Motivation

Understanding of poverty dynamics is important in designing social safety nets specially for cash transfer programmes. Economic status of potential and existing beneficiaries can exhibit poverty and non-poverty spell due to idiosyncratic or covariate shocks. Social safety nets as BISP, in case of Pakistan, intend to focus on the households that fall below the poverty line or Programme cutoff score.

Due to static nature of targeting method Programme, administration may incur potential exclusion error by excluding prospective beneficiaries who become poor due to shocks in time. Thus, poverty dynamics can affect eligibility for Programme benefits.

We can divide poor into two broad groups: transient poor and chronic poor. We can also identify usually-poor and always-poor within chronic poor group. Always-poor face obstinate poverty and their status do not change to non-poor overtime. Improvement in welfare of household occurs gradually but decline intents to appear abruptly. Usually poor or households which are slightly above the poverty threshold tend to fluctuate under and above the poverty line. Thus, they are considered ineligible for Programme.

Similarly, transient poor, who escape from poverty, may fall into poverty again. We can divide this group into two sub-groups occasionally and churning poor. Occasionally poor remain above the poverty line but face poverty spell at least once in a life (Hulme and Shepherd 2003). Churning poor experience poverty and non-poverty spell in a seasonal pattern, especially in rural areas (Dercon and Krishnan 2000).

Figure 1 explains the poverty dynamics of households over the time and their repercussion for the implementation of social safety nets. On the vertical axis, poverty threshold separates households from the non-poor households. Horizontal axis denotes time line which is divided into six hypothetical scenarios according to observed pattern of household income. Solid line represents the income level of household over the time.

Source: Juan M. Villa and Miguel Nino-Zarazua (2018)

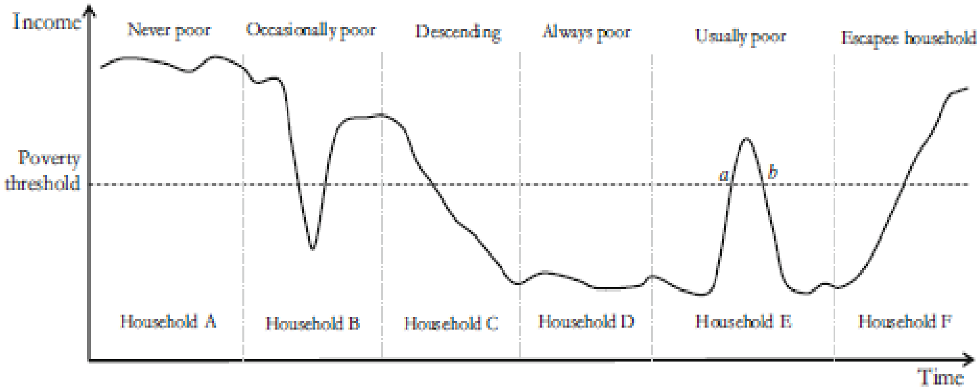


Figure 5.1: Poverty Dynamics (Hypothetical)

As figure shows income level of household A is above the poverty threshold and classified as never poor. Household B is initially non-poor but due to economic or climate shocks, it becomes poor for the short period and escape from poverty over the time, if it is provided social assistance. While descending household C might have witnessed a severe negative shock that strapped it below the poverty threshold. If the social safety net administration or designer do not incorporate the shocks in the targeting method household B and C would not be eligible for social assistance due to design exclusion error in targeting method. Always-poor (Household D) is persistently below the poverty line and eligible to social assistance. Household E is tenaciously poor over the time, although it may enjoy a short non-poverty spell in the long run. A social safety net, as BISP would stop the transfer to a usually poor household at point *a*, despite the fact that it would eventually fall into poverty at point *b* and become eligible for social assistance again. Administration of Programme would incur exclusion errors if usually poor households are excluded from the Programme at point *a*. If social safety net administration and Programme designers are able to estimate welfare level of the households in presence of economic and climatic shocks, they could prevent the exclusion of transient poor from the Programme.

5.1.3 Specified Objectives of Underlying Essay

Due to occurrence of covariate shocks, literature shows its negative impacts on poverty, which enhances the possibility that households which were not eligible for BISP, may become eligible over the time due to economic and climatic shocks. Similarly, there is a possibility that a household that entered in BISP at a certain level of welfare may not need assistance following a significant positive shock. Targeting method followed by BISP is static in nature and does not capture the dynamic of poverty due to shocks. Hence, following are the specified objectives of this essay:

1. To calculate a shock-adjusted PMT score to capture the dynamic nature of poverty in Pakistan.
2. To calculate the exclusion and inclusion errors from shock-adjusted PMT score.
3. To suggest the policy recommendation on the basis of obtained findings.

5.1.4 Significance of the Underlying Essay

A large segment of Pakistani society is highly vulnerable to different shocks and it can fall below the poverty line. BISP base line survey shows that households face different types of shocks, individual level (idiosyncratic shocks) and the entire community level (covariate) shocks. Thus, the nature of poverty in Pakistan is dynamic (Arif, Iqbal et al. 2011), (Arif and Bilquees 2007), and (Arif and Farooq 2014) there is a possibility that households which were not eligible for BISP, may become eligible over the time due to economic and climatic shocks. Similarly, there is a possibility that a household that entered in BISP at a certain level of welfare may not need assistance following a significant positive shock. Targeting method followed by BISP is static in nature and it doesn't capture the dynamic nature of poverty due to shocks. Thus, this study aims to introduce a new targeting method which is shock adjusted and capture the dynamic nature of poverty in Pakistan.

The subsequent parts of the underlying chapter comprise: section 5.2 deals with the literature review, section 5.3 deals with the targeting approaches, section 5.4 deals with the data description and methodological framework, section 5.5 deals with the results and discussion and section 4.6 deals with concluding remarks on the underlying chapter.

5.2 Literature Review

Targeting is a tool which policymakers use to make a said Programme efficient. It is not the end itself but it depends how much policymaker wants to target. Through efficient targeting, policymaker can benefit the poor or the subset of poor of the society in given resources. Thus targeting is attractive tool for policymakers in safety nets programmes (Grosh, Del Ninno et al. 2008). Means test accurately measures the earning of households and it is an excellent tool to target the poor. Practically, the means test suffers from several problems, i.e., households have incentive to understate their wealth to get enrolled in the target group. The verification is also difficult in the developing countries because the documented data is limited. With these practical and administrative difficulties of means test, the concept of proxy means test is much appealing. Proxy means test uses households' characteristics to determine the household income. Proxy means test is attractive because it is a good predictor and it can easily be verified (Narayan and Yoshida 2005). In comparative study of targeting in Latin America, (Grosh 1994) said that among all targeting methods proxy means test is the best for targeting in developing countries. Through household survey of different countries, (Persaud) showed that some variables, which are easy to collect, can be used as a proxy for the measurement of caloric adequacy. As it is said that the direct measurement of caloric adequacy is difficult to collect. Similarly, (Glewwe and Kanaan 1989) applied regression analysis on the data of several variables of Cote d'Ivoire to determine the welfare level. They establish that through regression policymaker can improve the targeting. (Grosh and Glinskaya 1997) applied regression on Armenia data to demonstrate that cash transfer Programme targeting can be improved significantly through proxy means test. Using the data set of living standard measurement survey of Bolivia, Jamaica and Peru, (Grosh and Baker 1995) carried out different simulations to explain that how different information can be used as proxy means test. (Brown, Ravallion et al. 2018) checked the efficiency of proxy means test by using the data of nine different African countries. They revealed that proxy means test helps to filter out non poor, but it suffers from exclusion error. They concluded that even with sufficient budget, existing targeting methods are unable to reach the poor. (Kidd and Wylde 2017) assessed the targeting effectiveness of proxy means test. They demonstrated with evidence that PMT is arbitrary and inaccurate method for targeting the poor. They were of the view that due to infrequent surveys, design and implementation errors, PMT cannot capture the dynamic nature of poverty. Thus, it creates unrest and conflict within communities. (Sharif 2009) built proxy means test by using survey data of household demographics and characteristics for Bangladesh. Author established that proxy means test significantly improves the targeting as compared to other existing targeting methods. But there are some challenges in implementation and management of information. (Sebastian, Shivakumaran et al. 2018) used household income and expenditure survey to develop proxy means test for Sri Lanka and they checked its effectiveness in ongoing Samurdhi Programme. They established that effectiveness of Samurdhi Programme can be increased by switching from self-reporting to proxy means test targeting.

To check effectiveness of proxy means test, and household economy analysis, (Schnitzer 2016) used panel data of Niger and found that PMT is better to target chronically poor, while HEA performs better in targeting seasonally food insecure households. Author suggests that combination of PMT with HEA and principal component analysis (PCA) can serve better for making integrated registry of the poor. (Coady, Grosh et al. 2004) accessed different social safety net programmes across the world. They found that the median social nets deliver about 25 percent more funds to the deprived people. They are of the view that there is no clear ideal targeting method. They explained that 80 percent variations in targeting performance are due to differences in targeting tools and 20 percent variations are because of differences across the targeting tools. (Ahmed and Bouis 2002) developed proxy means test for the targeting of food subsidies in Egypt. They found that forty-eight percent of high subsidy (green) card holders were non-poor and forty-two percent of low subsidy (red) card were needy. Thirty-two percent of households were not given any card. With the help of proxy means test, they brought equity in food subsidy system and saved LE 31 million. (Conning and Kevane 2002) highlighted that communities differ in their knack to device effective monitoring system and mobilize information. This might be cost saving or another avenue of rent seeking and corruption opportunity at local-level. Communities vary in their willingness to target the poor. At national level, there are complex political and economic issues that can undermine the social safety nets. Authors also reported that there are many practical and conceptual issues in community based targeting. (Castañeda, Lindert et al. 2005) explained that household targeting system and data collection should be designed carefully. Consolidated national database and proper identification is important. To avoid ghost beneficiaries and fraud, updating of data registry is crucial. The choice of household targeting mechanism also depends upon many factors like administration, cost and technical feasibility. Authors found significant variation in household targeting systems of six countries. They found that targeting system of Chile and Mexico perform better in terms of transparency, cost effectiveness and targeting outcomes. The registries in the United States of America perform excellent in terms of transparency and targeting outcomes but they are extremely expensive. Brazil and Columbia are strengthening their registries to improve their performance. As one size doses not fit for all. Different targeting tools are adopted by different countries. It is not the end itself but it depends how much policymaker wants to target. Targeting performance depends on the administrative and policymaker objectives, what they want to achieve in short or long run. As literature suggests that different countries adopted different targeting tools, like geographical targeting to community-based targeting, or mix of two or more tools, as the situation demands. In case of Pakistan, BISP is using static PMT targeting method, and it does not capture the impact of shocks on household welfare. Thus, we will try to fill this gap in this essay.

5.3 Targeting Approaches

To identify potential beneficiaries of social safety nets there are various well established targeting mechanisms. (Coady, Grosh et al. 2004) and (Grosh, Del Ninno et al. 2008) presented the merits and demerits of various methods like community based targeting, geographical targeting, demographic targeting, mean targeting and proxy means targeting. A large share of social safety nets benefits going to bottom two quintiles by using above-mentioned targeting methods. Community-based and proxy means selection of poor show better results but considerable variations are due to implementation strategy (Coady, Grosh et al. 2004). Following methods are the common targeting approaches used in literature to identify the poor for the social safety nets: (a) Geographical targeting, (b) Community-based targeting, (c) self-targeting, (d) mean testing (e) proxy mean testing (f) Hybrid method

5.3.1 Geographical Targeting

In geographical targeting, location is used to identify the poor for social safety net benefits. Individual or household living in the defined area especially poor, food insecure or natural disaster effect will be selected for the benefits and others will be excluded. Geographical targeting is also used as budgetary sharing tool, where the regions with high levels of poverty concentration receive greater share than the other regions.

Key problem of using geographical targeting is the geographic determination, used to select the area or region (province or district). Household income and expenditure surveys at the national level can be used to identify the occurrences of food insecurity or malnutrition in security or poverty. But the ability to select the small geographical area with high level of poverty is limited through the nationally representative household's surveys. Like, in case of Pakistan Household Integrated Expenditure Survey (HIES) can be used to identify poor areas at national level. On district level Pakistan Social and Living Measurement Survey (PSLM) can be used for poor. But the disparities in household circumstances within these far-reaching geographical areas are likely to be higher. By imputing consumption with survey data, geographical targeting can be achieved at the small area level (Alderman et al.,2003). In areas that are exposed to covariate shocks like drought, earthquake or flood, geographical targeting can be used to address the short-term needs of the households. In covariate shocks, even all households are exposed to shocks, but still there are some households which have enough resources to cope with the shocks. Thus, due to above-mentioned demerits, geographical targeting is often combined with other targeting approaches to identify the poor for selection in social safety nets.

5.3.2 Community-Based Targeting

In community-based targeting community notables or a group of community members are asked to identify the households, who are poor and eligible for the said social safety Programme.

Major advantage of community-based targeting is that it is based on local informal, which is easy to collect and less expensive as compared to other methods. It can be used not only for short-term interventions but also for chronic poverty. Safety nets that deal with chronic poverty require cohesive and clearly defined community structure for targeting. CBT can produce extensive Programme support even Programme benefit a small portion of the populations. In case of covariate shocks like earthquake, drought or other natural disasters, CBT can rapidly identify the affected households or individuals (World Bank 2013). But the main disadvantage of CBT is that, it is vulnerable to elite capture, and eligibility decisions can lack transparency.

5.3.3 Self-Targeting

In self-targeting, social safety nets are open to everyone. Those with high level of need will get enrolled in safety net programmes. Like in public work programmes wages are set too low, so the Programme is attractive only to those who are willing to work at that wage. After the economic crisis, Korea in 1997 and Argentina in 1999 used this method to alleviate poverty. After tsunami in 2005, Sri Lanka used self-targeting for employment generation and to support reconstruction. Literature shows that self-targeting is the suitable method for the short-term interventions in the time of economic crisis or natural disaster. Self-targeting can be used to improve targeting efficiency in prolong interventions (Alatas, Banerjee et al. 2013). Safety nets like Oportunidades in Mexico and National Rural Employment Guarantee Act in India combined the self-targeting with the proxy means test. Stigma and lack of Programme knowledge may discourage participation.

5.3.4 Means Testing

Most thorough approach to target the household is the means testing. Means testing can produce accurate results, if the underlying information on income or expenditure is correct. The method is administratively challenging. As in means testing potential beneficiary household's actual welfare is matched with the established threshold of Programme. Main disadvantage of means test is; household has incentive to underreport welfare measure, like income or expenditure to get enrolled in the Programme. To overcome underreporting, effective verification system must be in place. Situation becomes more problematic in underdeveloped and developing economies where formal documentation is not available. Like in African countries means testing is not suitable, as it becomes too costly to verify household well-being. It is also used to identify vulnerable households, like malnourished children. In this case potentially malnourished population children height and weight is measured to select malnourished. Means testing is attractive, as it can rapidly identify households that become food insecure due to idiosyncratic or covariate shocks. But there is inherent ambiguity in measuring food security, as subjective measures of food security are susceptible to manipulation. Also, expensive to collect income or consumption data for all potential beneficiaries.

5.3.5 Proxy Means Test

In proxy means test a proxy of household actual welfare is generated through easy to observe individual or household characteristics. Informal economies with high level of poverty which has no formal information household welfare can generate proxy of welfare by using statistical model. Easy observable indicators, like household demographics, durables, productive assets, location dwellings characteristics which are highly correlated with income or expenditures are used in statistical model to predict household welfare. On the prediction of welfare, household whose welfare falls below the threshold or cutoff score can be identified as poor. Advantage of using proxy test is that it offers fairly better targeting results for poor households with limits amount of information. Also, households do not know which variable is used in model, so they cannot underreport to under value their welfare level to get enrolled in the Programme. But PMT generate a great deal of suspension, as it relies on inference rather than direct scrutiny of information. PMT performs better in long-term targeting as compared to short-term targeting. Other criticism on PTM is because of inclusion or exclusion errors due to which household's classification become inaccurate. Proxy means tests are static in nature and do not capture the dynamic nature of poverty as poor are vulnerable to different shocks.

5.3.6 Hybrid Method

Literature shows that a mix of different targeting tools can be used in a single social net Programme. A combination of different tools can generate better results as compared to single targeting tool (Grosh, Del Ninno et al. 2008); (Handa, Seidenfeld et al. 2020). In Brazil's Bosla Familia Programme uses means testing with geographical targeting. Similarly, Oportunidades in Mexico, Orphan Vulnerable

Children Programme in Kenya uses geographical and mean testing jointly. Community based targeting, geographical targeting and proxy means testing is used jointly for targeting in Tanzania.

As it is evident from above discussion that no targeting method is perfect. A method does not fit for all as the capacity and choice depends on country specific needs. There are merits and demerits of each targeting tool. A method does not fit for all as the capacity and choice depends on country specific needs. Elite capture, underreporting of welfare and unviability of detailed microdata are the major demerits of community-based and means testing. But PMT allows for transparent, homogenous, and enforceable beneficiary selection rules. Thus, we advocate the proxy means test adjusted with different types of shocks i.e., climate (precipitation and temperature shocks) and macroeconomic shock (price shocks).

5.4 Data Description and Methodological Framework

This section is with data sources, measurement unit, variable description and methodological framework.

5.4.1 Data Sources

Data source for the proposed targeting method is Household Integrated Economic Survey 2018-19. HIES 2018-19 is the latest and updated national representative household survey of Pakistan, which consists of geographical location, dwelling characteristics, durables and productive assets and comprehensive household expenditure information of household. Detailed information about household expenditure is important for targeting of income. By using latest HIES data, we can capture poverty trends and its relationship with observable household characteristics. As poverty has dynamic nature and household’s socio-economic patterns evolve over time. Thus, observable household characteristics that matter for poverty outcomes are likely to change and the strength of the relationship with poverty outcomes is also likely to change. Calculating targeting mechanism on the older data set, one may inaccurately predict poverty outcomes.

5.4.1.1 Data Description

Selection of variables to new targeting formula is done on the basis of three main criteria: (a) easy to observe (b) sufficient frequency (c) strong correlation with welfare indicator consumption in our case. Data description is given below and in table 5.1.

Welfare Indicator

To capture dynamic nature of poverty and to update targeting mechanism we used consumption indicator adjusted for household size, composition and spatial differences in prices is used as welfare indicator. As needs vary among household members of different age and there are economies of scale in consumption. Thus poverty measures based on the per capita welfare indicators is misleading and biased as lager households would be preferred at the cost of smaller households. An alternative of per capita welfare indicator to base poverty measure is the expenditure per adult equivalent. Per capita consumption divides household consumption by the number of household members, while expenditure per adult equivalent considers households demographic structure in the calculating welfare indicator. In per adult equivalent method children and adults are given different weights. In Pakistan Poverty Reduction Strategy Paper children aged up to seventeen years are given the weight of 0.8, while household members aged eighteen years and above are given a weight of 1. Difference in weights capture the fact that children have lower consumption than the adults. But we are using the weight of 0.8 for children aged up to thirteen years and weight of 1 for all other members of households. As it is evident that the needs of youth are closer to adults than the minor members of households. Thus, the welfare indicator-based expenditure per adult equivalent is given by the following formula

$$\text{Per adult equivalent consumption} = \frac{\text{Total household consumption}}{0.8 * \text{No of Childern} + 1 * \text{No of Adults}}$$

Demographic Variables

We have used expanded set of demographic variables for the proposed targeting formula. A variable on the number of elder (age 65 years and above) household members is included, as a result, household with high number of elders get lower score. The number of males aged 35 to 65 is also included to reflect the household Labour supply and experience in the Labour market, which is likely to generate higher earnings compared to households with more females and younger male individuals. This also allows to take into account the gender composition of the households which is likely to affect poverty outcomes. To capture the quality of job held by the members of household, a variable at least one member is employed as regular paid employee in the public sector. An indicator of adult literacy household size and its square is also included in the proposed targeting method.

Dwelling Characteristics

Variables on the dwelling characteristics, like material used in floor, roof and walls of household. Fuel used for cooking, heating and lighting is also used. Source of drinking water is included with pipe, mineral and filtration plant water as reference category. Other categories have negative weight, which means household do not have this source of drinking water, will obtain lower score. Landline connection or mobile phone and type of toilet is also included.

Durables

We used an expanded set of durables of household like heater, fridge, fan, air cooler, car and motorcycle. Durable like geyser and air conditioner, television and videocassette recorder, cooking range and cooking stove are merged, as they have small frequencies.

Productive Assets

Two different types of productive assets: land and animals are included in proposed targeting method. Land is classified in two indicators. First is owning land between one acre to five acres and second indicator is owning five or more acre of land. To get sufficient precise estimates and their ability to predict consumption, categories are determined on the basis of having sufficient number of households in a given category. Owning at least one buffalo or at least on cattle animal also increases the PMT score, and the former has a larger impact on the PMT score than the latter. Owning land between 1 to 5 acres will increase welfare score by 0.06 as compared to household who do not own land, while household owning 5 or more acre of land will increase PMT welfare score by 0.133 as compared to household with no land. Household owning at least one buffalo or cattle will increase welfare score by 0.871 and 0.0597 respectively.

Geographical Locations

Urban and location status is also included in the model. Results show that household in urban area receive lower score by 0.03. The agro-climatic zones established by the National Agricultural Research Center (NARC) also significantly affect the PMT score. District in NARC zone dummy 1, 2 and 3 receive score 0.12, 0.53 and 0.09 higher as compared to reference category zone 4 mainly consisting the districts of

Punjab. Similarly, districts in NARC dummy 5, 6 and 7 increase the welfare by 0.08, 0.13 and 0.11 as compared to reference category zone 4. While in shock adjusted model, we have included only NARC 4th, 5th and 6th zone dummies. Zones detail is given in appendix.

Climatic Shocks

Climatic shocks like precipitation and temperature shocks adversely affect household well-being. Household living arid climate zone are susceptible to climatic shocks. As drier or colder than average climate negatively affects the household well-being; per adult equivalence consumption in our case. Similarly, less than average precipitation decreases agriculture productivity and more than average precipitation affects plantation and harvesting and also translate into flooding. Flooding has devastating effects on large scale. Thus, climatic shocks decrease household consumption. Coefficient of precipitation shock and temperature shocks are negative, lower the PMT score. Climatic shocks are calculated by the following formula:

Climatic shock = Current year Value – long run average

Table 5.1: Variables Names and Definitions

	Variable name	**Variable description**	Source *Section HIES-2018-19
Demographics	elderly_n	Number of household members aged 65 and above	Section1M,PartA,Q6
	depratio55	Dependency ratio, defined as : Number of members aged<=14 + Number of members aged>=65)/Number of household members, is >=0.55 & <0.65	Section1M,PartA,Q6
	depratio65	Dependency ratio, defined as: Number of members aged<=14 and below+ Number of members aged>= 65)/Number of household members, is >=0.65	Section1M,PartA,Q6
	overcrowd	Number of household members/Number of rooms in the dwelling	Section1,5M,PartA,Q1,3
	Household size	Number of household members	Section 1M PartA,Q1

	Household size_sq	Number of household members squared	Section 1M PartA,Q1
	n_male_3565	Number of males with age>=35 & age <65	Section 1M PartA,Q4 &Q6
	frac_lit	Share of individuals aged 15-64 that can read in any language: Number of members that can read/ Number of household members with age>=15 & age<=64	Section 2M PartA,Q1
	Public employee	At least one member employed as regular paid employee in the public sector	Section 1M PartB,Q5
Dwelling Characteristics	toilet flush	The household has flush toilet	Section 5M,PartA,Q21
	water2	Main water source is hand pump or others	Section 5M,PartA,Q11
	water3	Main water source is motorized pump or tube well	Section 5M,PartA,Q11
	water4	Main water source is open well, spring, closed well, tanker, river or canal	Section 5M,PartA,Q11
	Roof_1	Roof is made from wood/bamboo/metal/tin/girders/T-Iron	Section 5M PartA,Q6
	Roof_2	Roof is made from RCC/RBC/iron/cement sheets	Section 5M PartA,Q6
	Floor_1	Floor is made from earth/sand/dung	Section 5M PartA,Q5
	Floor_2	Floor is made from ceramic/marble/chips/polish wood/cement	Section 5M PartA,Q5
	Wall_1	Wall is made from raw bricks/mud/wood/bamboo	Section 5M PartA,Q7
	Wall_2	Wall is made from burned bricks/blocks/cardboard	Section 5M PartA,Q7
	CookingF_1	fuel is fire wood/ crop residual/coal	Section 5M PartA,Q8
	CookingF_2	fuel is gas/LPG/electricity	Section 5M PartA,Q8
	Lighting_1	Lighting fuel is kerosene oil/candle/other	Section 5M PartA,Q10
	Lighting_2	Lighting fuel is electricity/ solar energy/gas	Section 5M PartA,Q10
	Heating_1	Heating fuel is crop residue/dung cake/no facility.	Section 5M PartA,Q9
	Heating_2	Heating fuel is electricity/LPG/Gas/Bio gas	Section 5M PartA,Q9
	Tel	The household has a telephone connection	Section 5M,PartA,Q30
Durables	Heater	The household owns one heater or more	
	TV/VCR	The household owns one or more TV or/and one or more vcr	
	Fridge	The household owns one or more fridge	
	Freezer	The household owns one or more freezer	

	Washing machine	The household owns one or more washing machine	Section 7M, Q1
	Air cooler	The household owns one or more air cooler	
	Geyser/Air conditioner	The household owns one or more geyser or/and one or more air conditioner	
	Fan	The household owns one or more fans	
	Cooking stove/cooking range	The household owns one or more cooking stove or/and one or more cooking range	
	Car	The household owns one or more car	
	Only motorcycle	The household owns one or more motorcycle but no car	
Productive Assets	Buffalo	The household owns one or more buffaloes	Section 10M,PartB
	Cattle	The household owns one or more cattle animals	
	land_1	The household owns at least 1 acre but less than 5 acres of land	Section 10M,PartA
	land_5	The household owns 5 acres of land or more	
Geographical Location	urban	The household lives in an urban area	Cover Page
	narc_zone_d1	The household lives in a district in Zone 1 or Zone 9 of NARC classification	
	narc_zone_d2	The household lives in a district in Zone 2 of NARC classification	
	narc_zone_d3	The household lives in a district in Zone 3 of NARC classification	
	narc_zone_d5	The household lives in a district in Zone 5 of NARC classification	
	narc_zone_d6	The household lives in a district in Zone 6 or 7 NARC classification	
	narc_zone_d7	The household lives in a district in Zone 8 or 10 NARC classification	
Interactions	narc_zone6_urb	narc_zone_d6*urban	
	overcrowd_urb	overcrowd*urban	Created from Variables above
	heater_urb	heater*urban	
	narc_zone2_over	narc_zone_d2*overcrowd	
	narc_zone7_over	narc_zone_d7*overcrowd	
	narc_zone6_over	narc_zone_d6*overcrowd	
	narc_zone7_lit	narc_zone_d7*frac_lit	
	narc_zone2_lit	narc_zone_d2*frac_lit	
	Temperature Shock	Current year temperature- long-run average temperature	European Centre for Medium-Range Weather

			Forecast
Macroeconomic and Climate Shocks	Precipitation Shock	Current year Precipitation –long-run average precipitation	European Centre for Medium-Range Weather Forecast
	Flood Shock	Current year Value -long- run average value	NASA MODIS Satellite Data

5.4.2 Empirical Methodological Framework

This subsection deals with the technical debate on the methodology used in underlying study. Model construction and score cutoff point for eligibility criteria are given below:

5.4.2.1 Construction and Estimation of PMT (Technical Debate)

There are two main components that are involved in creating a proxy means test. First component is the formation of a model that regress the indicator of household welfare on household's characteristics like location, demographic dwelling, durables and productive assets etc. These household's characteristics are taken from nationally representative household integrated expenditure survey.

Household characteristics or covariate are selected on the following criteria:

Data Availability: Household level characteristics are often available at nationally representative income and expenditure surveys. In the case of Pakistan, household integrated expenditure survey is available. On district level Pakistan social and living standard measurement survey is available.

Readily Observable and Verifiable Variable: Households have clear incentive to underreport information strategically to get enrolled in the social safety net programmes, like BISP in case of Pakistan. Thus, the variable selected for the model should be readily observable and verifiable, like structure of house and assets.

Highly Correlated with Household Welfare: Proxy means test is used to predict household welfare accurately. Goal of our exercise is not to deal with structural modelling to get unbiased structural parameters about the relationship between household characteristics and welfare. Our objective is to generate the most appropriate model to predict welfare. Therefore, the variables selected for statistical model should be highly correlated with the well-being.

In second component, we use the weights generated from the first step on the registry of potential beneficiaries to estimate predicted household welfare. In last step we determine the eligibility cutoff for Programme.

Statistical model is estimated by ordinary least squares (OLS) from the following equation:

$$C_i = X_i\,\beta + \varepsilon_i \quad \ldots\ldots\ldots\ldots\ldots\ldots.. \quad (5.1)$$

In equation 5.1, Ci is the expenditure of household i, Xi is a row vector of household characteristics, β is a vector of parameter estimates, and εi is the error term.

In the next step, vector of parameter estimates (β) are used as weights to predict welfare of household to screen for the social safety Programme. In this process data of potential beneficiary which is obtained in registration form is matched.

Here, a vector $\mathbf{Z_j}$ that has same variables as in $\boldsymbol{X_i}$ equation 5.1 is multiplied by **β** estimates of the parameter vector in equation 5.2 given below to accurately predict the welfare of household. If the predicted household welfare level falls below the threshold level of the Programme, household is selected as eligible for the Programme.

The PMT score and selection criteria is given as under:

$$\hat{C}_j = Z_j\hat{\beta} \ldots\ldots\ldots\ldots\ldots\ldots \text{(5.2)}$$

In equation 5.2 $\hat{\mathbf{C}}_{\mathbf{j}}$ denotes PMT score based on the predicted welfare level of household **j.** $\mathbf{Z}_{\mathbf{j}}$ is row vector of covariate taken from potential beneficiary. $\hat{\boldsymbol{\beta}}$ is the vector of parameter estimates from the equation 5.1.

Normalization PMT

After OLS estimations we predict household welfare, which is in fitted form. To normalize we used the following formula:

PMT normalization = [(actual Fitted Value-min FV)/(maxFV-minFV)] *100

Eligibility Criteria

Household j is eligible, if $\hat{\mathbf{C}}_{\mathbf{j}} \leq$ **cutoff**; it is ineligible if $\hat{\mathbf{C}}_{\mathbf{j}} >$ **cutoff**.

Drawback of Standard PMT

Proxy means test do not capture explicitly the household exposure to shocks. In standard PMT household, exposure to shock is not included as covariate, but as a part of error component of the statistical model. As households face different types of idiosyncratic and covariate shocks, a household which is above the threshold welfare level may fall below after exposure to shocks. Thus, we made slight changes in standard PMT to make it shock adjusted to capture the shock effects on household welfare. Proposed shock adjusted proxy means test in explained below:

5.4.2.2 Shock Adjusted Proxy Means Test

Shock adjusted proxy means test is variant of standard PMT that integrate the household exposure to shocks. Cross-sectional data is the best option for measurement of shock adjusted PMT. However, household welfare before and after shock cannot be measured with cross sectional data.

We can measure the impact of a shock from variations in consumption of households.

$$\mathbf{C_i = X_i\ \beta + S_i \alpha + \mu_i} \quad \ldots\ldots\ldots\ldots\ldots.. \quad \mathbf{5.3}$$

Where *Si* is measure of shock. This specification differs from the standard PMT, where household exposure to shock is implicitly the part of error term of the model. The key objective of the shock adjusted PMT is to generate accurate measures of α (impact of shocks) on the PMT score. Several alternative strategies are available. The most direct method is to add information on shocks directly into the PMT estimator. For instance, the impact of aggregate climatic shocks can be estimated using widely available, continent wide, and detailed geo-referenced information on historic rainfall from the NASA MODIS satellite data or from Centre for Medium-Range Weather Forecasts. Otherwise, variations in rainfall from historic trends can be employed to generate more nuanced estimates of climatic impacts on PMT scores. The advantages of this approach are that data on aggregate shocks are often readily available and the estimation methods are the same as those used in the PMT.

Second method is to add discrete variables of household exposure to shocks directly in the PMT regressions, as is done in Kenya and Malawi. The advantage of this approach is that estimations of α are based directly on PMT scores. Disadvantages are twofold. First, household surveys used in PMT estimation often do not have good information on household exposure to shocks. Second, reported household exposure to shocks may be endogenous—for a given shock, poorer households may be more likely to report exposure due to a poorer base of resources or weaker coping mechanisms. This may lead to biased estimates of the impact of shocks on PMT scores. A third approach builds on the second and uses an endogenous treatment effect model to account for possible endogeneity in the exposure to shocks. The advantages of this approach are that estimates of the impacts of a shock will be unbiased when the model is specified properly. There are two associated disadvantages. First, the estimation method is more technically complex. Second, valid exclusion restriction variables to identify the model (variables that are associated with exposure to shocks, but influence PMT measures only through their impact on exposure to shocks) are often difficult to obtain from survey data. Once the shock adjusted PMT model is estimated, Programme eligibility of a household after exposure to a shock is easily recovered by incorporating the weight associated with the impact of the shock *Si* into the PMT measure.

Households whose predicted welfare level $\mathbf{\hat{C}_j = Z_j\hat{\beta}}$ falls below the cutoff point are identified as poor. Households that are vulnerable to shocks are then identified by including exposure to shocks in the PMT calculation. This is done by adding α_ to the PMT score. Households whose welfare falls below the threshold level of Programme after exposure to a shock become eligible for safety net Programme. The shock adjusted PMT method clearly requires additional information on household exposure to shocks. Thus, it represents a "higher" level of information investments for targeting.

Eligibility Criteria of Shock Adjusted PMT

Household j is eligible, if $\mathbf{\hat{C}_j} \leq$ **cutoff**; it is ineligible if $\mathbf{\hat{C}_j} >$ **cutoff**.

5.5 Results and Discussion

This section deals with results estimated from the discussed model. Detail is given in the following sub-section:

Table 5.5.1A: Estimated Models for the Construction of PMT with and without Shocks

Variables	Without Shock Model	With Shock Model
Elderly	-0.0201***	-0.0194***
	(0.00440)	(0.00441)
depratio55	-0.0345***	-0.0363***
	(0.00583)	(0.00579)
depratio65	-0.0374***	-0.0380***
	(0.00586)	(0.00584)
Overcrowd	0.213***	0.210***
	(0.0181)	(0.0178)
Household size	-0.122***	-0.123***
	(0.00520)	(0.00525)
Household size_sq	0.00324***	0.00326***
	(0.000288)	(0.000292)
frac_lit	0.0196***	0.0201***
	(0.000974)	(0.000958)
Public employee	0.00862***	0.00899***
	(0.00149)	(0.00150)
toilet flush	0.0567***	0.0471***
	(0.00453)	(0.00453)
water2	-0.0495***	-0.0309***
	(0.00674)	(0.00669)
water3	-0.0484***	-0.0291***
	(0.00549)	(0.00551)
water4	-0.0326***	-0.0401***
	(0.00732)	(0.00721)
Tel	0.120***	0.127***
	(0.0187)	(0.0187)
floor_1	0.0215***	0.0328***
	(0.00767)	(0.00753)
floor_2	0.0688***	0.0757***
	(0.00736)	(0.00730)
wall_1	-0.0200***	-0.0259***
	(0.00598)	(0.00592)
roof_2	0.0699***	0.0678***
	(0.00544)	(0.00551)
heating_1	0.0193***	0.0178**
	(0.00720)	(0.00728)
heating_2	0.0279***	0.0293***
	(0.00798)	(0.00814)
lighting_1	-0.112***	-0.114***
	(0.00857)	(0.00830)
cooking_1	-0.0212***	-0.0271***
	(0.00639)	(0.00637)
TV	0.0210***	0.0250***
	(0.00491)	(0.00489)

Fridge	0.106***	0.106***
	(0.00538)	(0.00537)
Freezer	0.0992***	0.110***
	(0.0108)	(0.0109)
Washing machine	0.0457***	0.0452***
	(0.00522)	(0.00520)
Air cooler	0.0525***	0.0548***
	(0.00722)	(0.00717)
Geyser/air conditioner	0.199***	0.201***
	(0.00967)	(0.00964)
cooking/micro	0.185***	0.185***
	(0.0102)	(0.0102)
Car	0.310***	0.306***
	(0.0130)	(0.0129)
only motorcycle	0.107***	0.106***
	(0.00450)	(0.00449)
Buffalo	0.0871***	0.0932***
	(0.00603)	(0.00599)
Cattle	0.0597***	0.0484***
	(0.00579)	(0.00573)
land_1	0.0600***	0.0560***
	(0.00672)	(0.00666)
land_5	0.134***	0.132***
	(0.0103)	(0.0103)
Urban	-0.0367***	-0.0317***
	(0.0103)	(0.00998)
narc_zone_d1	0.121***	
	(0.00697)	
narc_zone_d2	0.0538***	
	(0.00781)	
narc_zone_d3	0.0921***	
	(0.00545)	
narc_zone_d4		-0.153***
		(0.00782)
narc_zone_d5	0.0850***	-0.0687***
	(0.00895)	(0.0105)
narc_zone_d6	0.133***	-0.0447***
	(0.0104)	(0.0121)
narc_zone_d7	0.114***	
	(0.0124)	
heater_urb	0.0365***	0.0487***
	(0.0115)	(0.0117)
overcrowd_urb	0.140***	0.138***
	(0.0201)	(0.0198)
narc_zone7_lit	-0.0112***	-0.0137***
	(0.00284)	(0.00225)
narc_zone6_urb	-0.0402***	

	(0.0144)	
Precipitation shock		-0.0155***
		(0.00371)
Flood shock		-0.0213***
		(0.0324)
Temperature shock		-0.0927***
		(0.000806)
Constant	8.523***	8.586***
	(0.0247)	(0.0261)
Observations	24,809	24,809
R-squared	0.696	0.698
To calculate PMT score, 1st we have estimated with and without shock model with OLS. From table we can see shock variable has significant negative impact. After that we have predicted PMT (fitted values). Through normalization we have calculated PMT score.		

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

5.5.1 Model Performance at National Level

Table given below (5.2), presents the model performance based on the Household Integrated Expenditure Survey 2018-19. Overall targeting performance of model is increased to 67 percent as compared to 60 percent previously. Coverage of bottom 20 percent from urban areas is decreased to 42 percent as compared to 55 percent previously. Urban areas were given over coverage in previous model adopted by BISP based on HIES 2013-14. As table shows, targeting performance of updated formula increased to 67 percent belonging to bottom 20 percent nationally as compared to 60.1 percent. Thus, targeting performance of new formula significantly increased.

Current updated targeting formula also brings distribution of eligible households closer to the actual distribution of poor across the provinces as shown in the following figure 5.2. In previous BISP targeting formula, the actual share of Punjab was lower than the actual poor. Now with updated formula, share is closer to actual poor (33.61 percent is actual figure and now share of beneficiaries from Punjab is 32.42 percent).

Table 5.2: Without Shocks Model Performance at National Level

Cover-age of total Population	Targeting-ng (% of beneficiaries that are poor, bottom 20%)	Targeting-ng (% of beneficiaries that are poor, bottom 40%)	Cover-age of the bottom 20 Population (%)	Cover-age of the bottom 20 Population (%)	Cover-age of the bottom 20 Population (%)	Cover-age of the bottom 40 Population (%)	Cover-age of the bottom 40 Population (%)	Cover-age of the bottom 40 Population (%)
National	National	National	National	Rural	Urban	National	Rural	Urban
5.00	82.37	97.95	17.83	19.65	9.67	10.98	12.67	5.16
10.00	77.00	95.07	33.33	36.15	20.71	21.31	24.40	10.73
15.00	71.67	93.19	46.53	50.19	30.20	31.33	35.63	16.57
20.00	66.98	91.04	57.96	61.52	42.05	40.80	45.48	24.70
25.00	62.61	88.61	67.76	71.12	52.75	49.66	54.71	32.34
30.00	58.30	86.14	75.72	78.96	61.22	57.94	63.21	39.82
35.00	53.98	83.44	81.78	84.35	70.31	65.47	70.55	48.03
40.00	50.22	80.67	86.97	88.89	78.34	72.34	76.88	56.72
45.00	46.72	77.70	91.00	92.55	84.03	78.38	82.48	64.26
50.00	43.48	74.56	94.10	95.22	89.11	83.57	86.99	71.80
55.00	40.49	71.42	96.41	97.18	92.97	88.07	90.86	78.47
60.00	37.70	68.28	97.93	98.31	96.23	91.85	93.89	84.83
65.00	35.14	64.95	98.89	99.20	97.51	94.65	96.11	89.64
70.00	32.81	61.64	99.42	99.61	98.53	96.73	97.83	92.95
75.00	30.69	58.33	99.65	99.74	99.22	98.07	98.73	95.82
80.00	28.81	55.21	99.78	99.87	99.38	99.01	99.43	97.61
85.00	27.13	52.21	99.83	99.90	99.51	99.48	99.70	98.73
90.00	25.64	49.47	99.91	100.00	99.51	99.81	99.93	99.39
95.00	24.31	46.93	99.97	100.00	99.81	99.95	99.98	99.82
100.00	23.10	44.60	100.00	100.00	100.00	100.00	100.00	100.00

BISP actual beneficiaries from Punjab are 39.44 percent. Currently, share of beneficiary households from Sindh is higher than the actual poor (30.42 percent actual poor in Sindh but beneficiaries from Sindh in BISP are 36.69 percent). Estimated beneficiaries from Sindh are 29.98 percent (figure5.4). 18.39 percent households from total poor household are from KPK (figure 5.2) and BISP beneficiaries from KPK are 19.84 percent (figure 5.3).

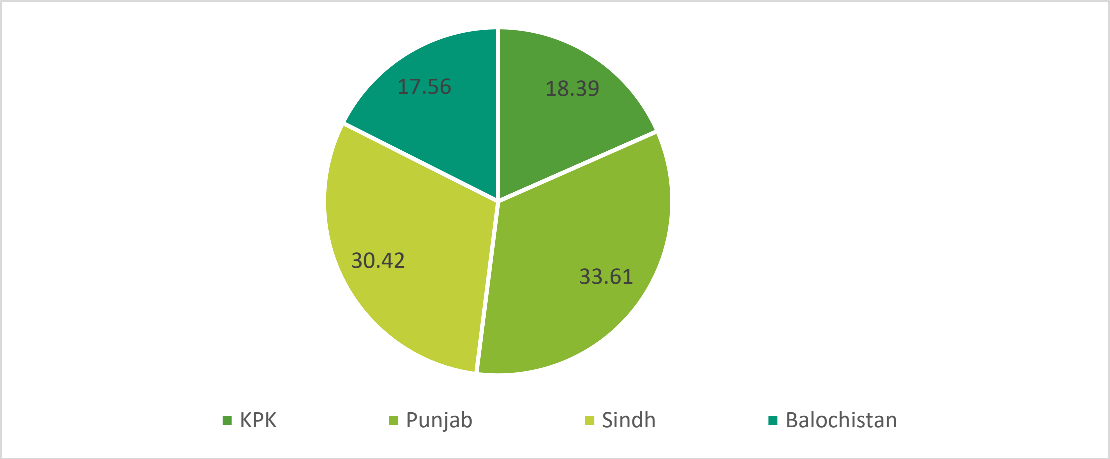


Figure 5.2: Relative Poverty by Provinces

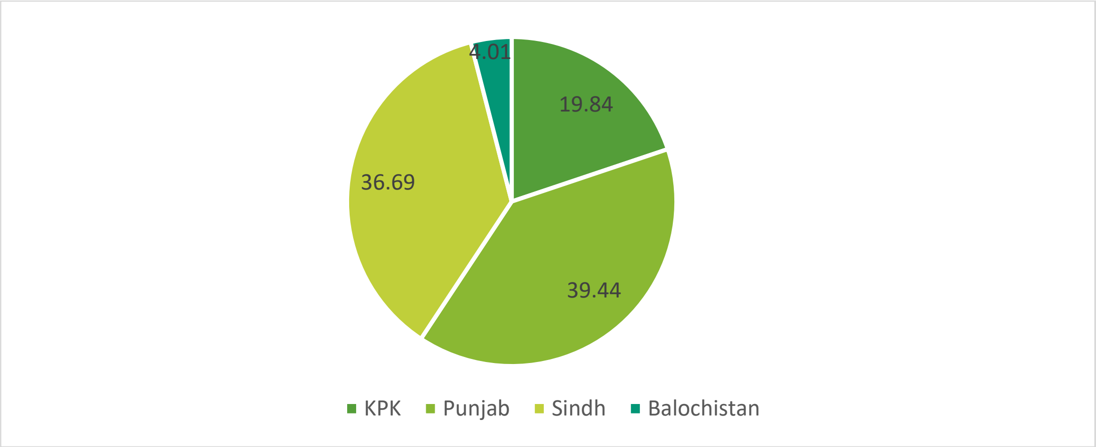


Figure 5.3: Province-wise BISP Current Eligibility

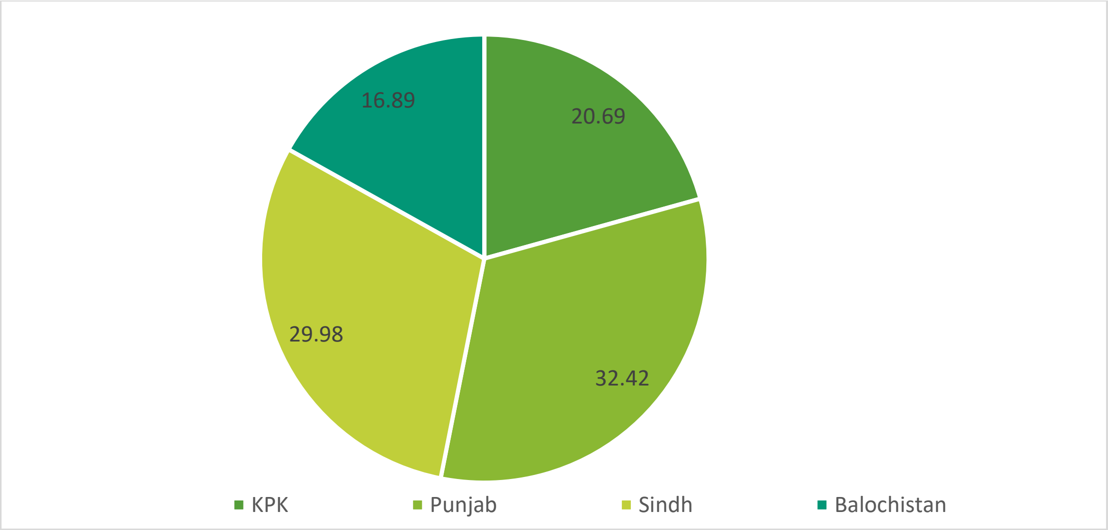


Figure 5.4: Province-wise Eligible from HIES 2018-19

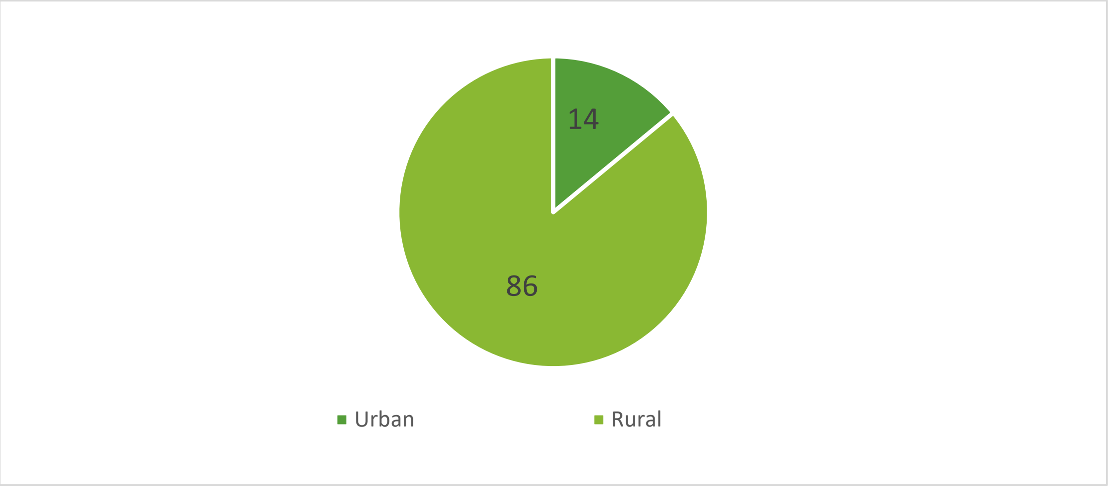


Figure 5.5: Region-wise BISP Current Eligible

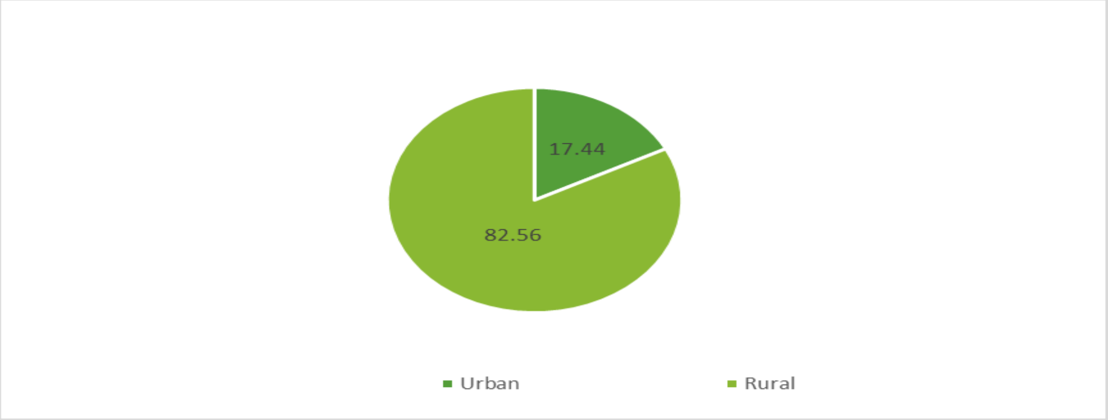


Figure 5.6: Region-wise Poverty

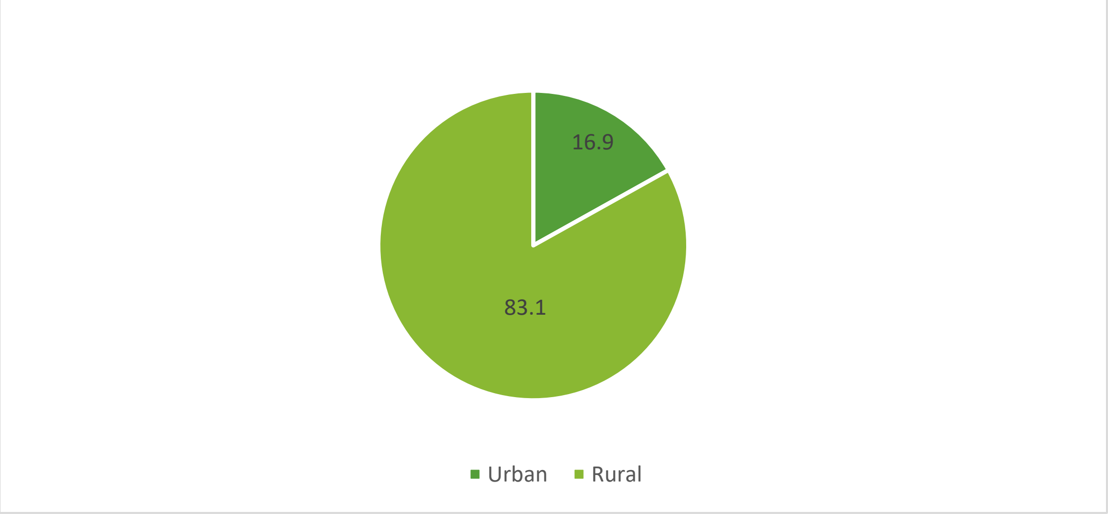


Figure 5.7: Region-wise Eligible from HIES 2018-19

Balochistan has highest poverty rate, but BISP targeting of poor household is low. Only 4.1 percent households are eligible in BISP from Balochistan as shown in figure 5.3. Current targeting formula from HIES 2018-19 identifies 16.89 percent households eligible for social assistance as compared to 17.56 percent actual poor in Balochistan as shown in figure 5.2 and figure 5.4. Current updated targeting formula also brings distribution of eligible households closer to the actual distribution of poor across the region. Figure 5.6 shows that 17.44 percent poor household reside in urban areas. BISP urban beneficiaries are only 14 percent as shown in figure 5.5. Updated formula identifies that 16.9 percent poor household are eligible from urban region as compared to actual 17.44 percent as shown in figure 5.6 and 5.7.

5.5.1.2 Targeting Performance of Model Across Provinces

Targeting performance of the updated model significantly increased not only nation-wide but also across provinces as shown in the following table. In case of KPK targeting of bottom 20 percent beneficiaries increased from 44.3 percent to 76.25 percent. This is significant targeting improvement. Similarly, in case of Punjab targeting of beneficiaries is from bottom 20 percent from 63.8 percent to 74.66 percent. In case of Sindh targeting of bottom 20 percent beneficiaries increased from 59.8 percent to 77.26 percent. While in case of Balochistan, targeting of bottom 20 percent increased from 65.9 percent to 74.77 percent. Thus, there is significant improvement of targeting bottom 20 percent beneficiaries that are poor across the provinces.

Table:5.3 Without Shocks Model Performance at Provincial Level

Level	Relative Poverty from HIES 2018-19	Cover-age of total Population	Targeting-ng (% of beneficiaries that are poor, bottom 20%)	Targeting (% of beneficiaries that are poor, bottom 40%)	Cover-age of the bottom 20 Population (%)	Cover-age of the bottom 20 Population (%)	Cover-age of the bottom 20 Population (%)	Cover-age of the bottom 40 Population (%)	Cover-age of the bottom 40 Population (%)	Cover-age of the bott-om 40 Population (%)
	All	**All**	**All**	**All**	**All**	**Rural**	**Urban**	**All**	**Rural**	**Urb-an**
KPK	27.00	14.45	76.25	92.83	37.83	38.77	29.64	25.47	26.45	18.10
Punjab	16.30	5.47	74.66	94.16	23.10	25.14	14.98	13.70	15.38	7.95
Sindh	24.60	14.65	77.26	95.78	43.60	49.85	22.04	29.35	38.20	10.34
Balochi-stan	40.70	36.02	74.77	95.89	61.44	64.34	47.68	47.65	52.26	30.32
Pakistan	21.50	20.00	66.98	91.04	57.96	61.52	42.05	40.80	45.48	24.70

5.5.2 Impact of Shocks on Household Welfare

Literature suggests that shocks either covariate or idiosyncratic negatively affect household welfare. Household welfare is estimated from PMT formula that ranges from 1 to 100. Lower PMT score represents low level of household welfare and higher PMT score represents higher level of welfare.

Table 5.4: Impact of Shocks on Log of PMT (Quantile and Linear Regression)

	25^{th}	50^{th}	75^{th}	OLS
Flood Shocks	-.0929963 *** (.0149617)	-.0510761*** (.0112176)	-.0394512*** (.0114314)	-.0727584*** (0.01114)
Rainfall Shocks	-.1090818 *** (.0052253)	-.0737206 *** (.0039177)	-.0615851 (.0039924	-.0879429*** (0.034397)
Temperature Shocks	-.0073453 *** (.0008173)	-.0049676 *** (.0006128)	-.0024932 .0006244	-.0042764*** (.005764)
Constant	2.243875 *** (.0279517)	2.643815*** (.020957)	2.956844 .0213563	2.594982*** (.0193865)
	Pseudo R2 = 0.0175	Pseudo R2 = 0.0113	Pseudo R2 = 0.0088	R-squared = 0.0229
Note: ***: p value<=0.01; **: p-value <=0.05; *: p-value <=0.10				

To check the impact of shock on household welfare, we have taken the log of PMT welfare score and applied quantile regression. Results in the following table shows that shocks severely affect household at bottom quantile. Negative effects of shocks gradually decrease in higher quantiles. Thus, the welfare of household at bottom quantile decreased and then the main victim of shocks. Household at bottom quantile which were slightly above the poverty line, now fall below the poverty line. Before the occurrence of shocks, they were not eligible for social assistance. Now they become eligible for the social assistance. We also estimated the impacts of shocks on household welfare by Ordinary Least Square (OLS). Results in the above table shows that due to flood shock household welfare decreased by the factor of 0.72. Precipitation shock welfare decreases by the factor of 0.087. Similarly, due to temperature shock, household welfare decreases by the factor of 0.0042.

5.5.3 Impact of Shocks on Different Welfare Quantiles

We have also checked the impact of shocks on different quantiles of household welfare. For this purpose, we have divided household welfare in five quantiles. 5th quantile is taken as the base category. 1st we estimated the impact of shocks by generalized order logit and then calculated odd ratios. Results in the following table show that bottom quantile is severely affected by the shocks, as compared to higher quantiles. Due to flood shock household probability to move higher quantiles decreases by 32 percent. Due to precipitation shock household probability to move higher quantiles decreases by 38 percent. Due to temperature shock probability to move higher quantiles decreases by 3 percent. In 2nd and 3rd quantile household probability to move to higher quantiles decreases by less percentage. In 4th quantile household probability to move higher quantile is less affected.

Table 5.5: Impact of Shocks on Different PMT Quantiles

Generalized Order Logit			Generalized Order Logit Odd Ratios		
PMT Quantile	Coefficient	Robust Std. Err.	pmt_quantile	Odds Ratio	Robust Std. Err.
Quantile1			**Quantile1**		
Flood Shock	-0.3821356***	0.0575588	Flood Shock	0.6824025***	0.0392783
Precipitation Shock	-0.4722671***	0.0240877	Precipitation Shock	0.6235869***	0.0150208
Temperature Shock	-0.0272694***	0.0034843	Temperature Shock	0.9730991***	0.0033906
_cons	-0.3241029***	0.1186844	_cons	0.7231758***	0.0858297
Quantile2			**Quantile2**		
Flood Shock	-0.2658712***	0.0524767	Flood Shock	0.7665379***	0.0402254
Precipitation Shock	-0.3843603***	0.0191184	Precipitation Shock	0.680886***	0.0130175
Temperature Shock	-0.0260848	0.0029806	Temperature Shock	0.9742525***	0.0029039
_cons	-1.100878***	0.1014899	_cons	0.332579***	0.0337534
Quantile 3			**Quantile 3**		
Flood Shock	-0.2254271***	0.0525943	Flood Shock	0.7981753***	0.0419795
Precipitation Shock	-0.359097***	0.0187956	Precipitation Shock	0.6983066***	0.0131251
Temperature Shock	-0.0207248***	0.0030151	Temperature Shock	0.9794885***	0.0029532
_cons	-1.720158***	0.1029202	_cons	0.1790379***	0.0184266
Quantile 4			**Quantile 4**		
Flood Shock	-0.1284602**	0.0616566	Flood Shock	0.8794486**	0.0542238
Precipitation Shock	-0.3418559***	0.022315	Precipitation Shock	0.7104506***	0.0158537
Temperature Shock	-0.0139436***	0.0036672	Temperature Shock	0.9861531***	0.0036164
_constant	-2.469379***	0.1253377	_constant	0.0846374***	0.0106083
Note: ***: p value<=0.01; **: p-value <=0.05; *: p-value <=0.10					

From above discussion it is proved that shock negatively affect household welfare. Current targeting method followed by the BISP does not capture impact of shocks. So, there is need to address this shortcoming in targeting method followed by the BISP. We have developed a new proxy means targeting method which capture the impact of shock on household welfare. Proposed method is standard variant of proxy means test with shocks. Shock adjusted model performance at national and across provinces is given in next section.

5.5.4 Shock Adjusted PMT Performance

Overall performance of shock adjusted model is slightly increased from 66 percent to 67.42 percent. Also, the coverage of bottom 20 percent population increased to 58.36 percent. Coverage of bottom 20 percent from rural areas also increased to 62.12 percent. Coverage of the bottom 20 percent population from urban areas decreases by 1 percent.

Table 5.6: Model Performance with Shocks at National Level

Cover-age of total Population	Targeting-ng (% of beneficiaries that are poor, bottom 20%)	Targeting-ng (% of beneficiaries that are poor, bottom 40%)	Coverage of the bottom 20 Population (%)	Coverage of the bottom 20 Population (%)	Coverage of the bottom 20 Population (%)	Coverage of the bottom 40 Population (%)	Coverage of the bottom 40 Population (%)	Coverage of the bottom 40 Population (%)
Nation-al	**National**	**National**	**National**	**Rural**	**Urban**	**Nation-al**	**Rural**	**Urban**
5.00	85.09	98.26	18.40	20.22	10.29	11.01	12.67	5.30
10.00	76.76	95.51	33.17	36.10	20.06	21.37	24.45	10.80
15.00	71.84	93.09	46.64	50.35	30.03	31.30	35.39	17.23
20.00	67.42	90.98	58.36	62.12	41.54	40.79	45.54	24.46
25.00	62.71	88.71	67.86	71.29	52.52	49.71	54.93	31.79
30.00	58.45	86.27	75.91	78.83	62.83	58.02	63.10	40.56
35.00	54.08	83.44	81.94	84.59	70.07	65.47	70.50	48.21
40.00	50.40	80.70	87.28	89.35	78.00	72.37	77.12	56.07
45.00	46.75	77.64	91.08	92.78	83.46	78.32	82.58	63.70
50.00	43.48	74.51	94.11	95.31	88.72	83.52	87.17	70.97
55.00	40.43	71.59	96.27	97.05	92.79	88.27	91.14	78.41
60.00	37.70	68.25	97.93	98.42	95.73	91.80	94.01	84.23
65.00	35.09	64.98	98.76	98.96	97.82	94.68	96.19	89.51
70.00	32.79	61.61	99.36	99.54	98.59	96.68	97.75	93.01
75.00	30.69	58.31	99.63	99.74	99.15	98.05	98.78	95.55
80.00	28.80	55.18	99.76	99.85	99.35	98.97	99.43	97.37
85.00	27.13	52.24	99.83	99.91	99.46	99.54	99.73	98.89
90.00	25.64	49.48	99.91	100.00	99.51	99.84	99.94	99.51
95.00	24.31	46.92	99.97	100.00	99.81	99.93	99.98	99.78
100.00	23.10	44.60	100.00	100.00	100.00	100.00	100.00	100.00

Table 5.7: Model Performance with Shocks at Provincial Level

Level	Relative Poverty From HIES 2018-19	Coverage of total Population	Targeting (% of beneficiaries that are poor, bottom 20%)	Targeting (% of beneficiaries that are poor, bottom 40%)	Coverage of the bottom 20 Population (%)	Coverage of the bottom 20 Population (%)	Coverage of the bottom 20 Population (%)	Coverage of the bottom 40 Population (%)	Coverage of the bottom 40 Population (%)	Coverage of the bottom 40 Population (%)
	All	All	All	All	All	Rural	Urban	All	Rural	Urban
KpK	27.00	14.89	76.45	92.99	39.08	40.08	30.30	26.28	27.29	18.74
Punjab	16.30	4.79	75.57	95.46	20.50	22.61	12.07	12.17	13.77	6.69
Sindh	24.60	16.94	76.27	95.61	49.74	56.78	25.46	33.87	44.01	12.07
Balochistan	40.70	33.52	75.56	95.99	57.79	60.98	42.68	44.40	48.95	27.27
Pakistan	21.50	20.00	67.42	90.98	58.36	62.12	41.54	40.79	45.54	24.46

While at provincial level targeting performance slightly increase in KPK and Punjab. In case of Sindh and Balochistan slightly decreases. Coverage of the bottom 20 percent population increases by 2 percent as compared to without shock model in KPK. In case of Punjab coverage of bottom 20 percent population decreases by 3 percent as compared to without shock model. While in case of Sindh coverage of bottom 20 percent population increases by 6 percent. In Balochistan coverage of bottom 20 percent population decreases by 2 percent as compared to without model.

5.5.5 Performance Measures

There are some built-in measurement errors in Proxy Means Test like error of inclusion and error of exclusion. Actual household consumption of household is more accurate level of welfare as compared to PMT based welfare. If the household consumption is below the poverty line but above the PMT cutoff score, we take it as exclusion error. Contrary, if household consumption is above the poverty line but below the PMT score, we take it as exclusion error ((Grosh 1994); (Grosh and Baker 1995); (Narayan and Yoshida 2005); (Sharif 2009)). Measure of performance is calculated by the formulas given in the following table.

Table 5.8: Inclusion and Exclusion Errors based on 2nd Quantile Level

		Household Actual Welfare (Based on consumption)		
		Poor	Nonpoor	Total
Estimated Welfare of Household	Poor	Successful Targeting (S1)	Inclusion Error (E2)	Total Eligible (N3)
	Nonpoor	Exclusion Error (E1)	Successful Targeting (S2)	Total Non-Eligible (N4)
	Total	Total Poor (N1)	Total Nonpoor (N2)	Total Population (N)
Coverage = S1/N1, Targeting = S1/N3, Total Coverage = N3/N, Exclusion error = E1/N1, Inclusion error=E2/N3				

Our shock adjusted targeting model successfully identifies 70 percent poor from the bottom 2 quantiles. Inclusion error of the model is 29 percent. Exclusion error is 29.86 percent. 58.83 percent nonpoor are correctly identified. Coverage rate of model is 70.1 percent. Targeting rate is 70.99 percent.

Table 5.9: Without Shock Model Actual Inclusion and Exclusion Error

		Household actual welfare (Based on consumption)		
		Poor	Nonpoor	Total
Estimated Welfare of Household	Poor	3017 (67.85%)	1375 (31.30%)	4392
	Nonpoor	1429 (32.14%)	1720 (55.57%)	3149
	Total	4446	3095	7541
Coverage = 67.85%, Targeting = 68.69 %, Total Coverage = 58.24%, Exclusion error =32.14%, Inclusion error = 31.31%				

Table 5.10: Shock Adjusted Model Actual Inclusion and Exclusion Error

		Household Actual Welfare (Based on consumption)		
		Poor	Nonpoor	Total
Estimated welfare of household	Poor	3118(70%)	1274(29%)	4392
	Nonpoor	1328(29.86%)	1821(58.83%)	3149
	Total	4446	3095	7541
Coverage = 70.13%, Targeting = 70.99%, Total Coverage = 58.24%, Exclusion error =29.86%, Inclusion error = 29%				

5.5.6 Testing the Consistency of the Shock –Adjusted PMT

To test the consistency of the shock-adjusted PMT, we have randomly split the sample into two equal parts: Testing sample, and Training sample. We actually run training sample. Predict PMT. The coefficients are then multiplied with testing sample variables in Stata to generate PMT score. After that we have found the mean difference between both training sample PMT and testing sample PMT.

Table 5.11: Testing the Consistency of the Shock-Adjusted PMT

	Obs.	**Average PMT**	**Std. Err.**
Training Sample	12,404	19.43	0.003685
Testing Sample	12,404	19.44	0.003737
Mean Difference		-0.01	0.00525
T-statistic	**-1.1913**		
P-value	**0.2336**		
Note: The mean difference is found statistically insignificant, which means there is no significant difference between both PMT's. We can conclude that on the whole model we have designed to calculate shock-adjusted PMT score is working effectively.			

5.5.7 Policy Analysis based on Different PMT Cutoff

For policy suggestions we simulated different PMT (with and without shock) based on HIES (2018-19) data. Results are given in the following table:

PMT Cut off 10				
Model	**No. of Eligible**	**% of Survey Population**	**Eligible Population (Millions)**	**Financial Burden (Billions) (5000 one time)**
Without shock	1807	7.2	15.84	79.20
With shock	2053	8.2	18.04	90.20
PMT Cut off 12				
Without shock	3334	13.44	29.57	147.85
With shock	3716	14.97	32.93	164.65
PMT Cut off 15				
Without shock	6838	27.56	60.63	303.15
With shock	7366	29.70	65.34	326.7
Through different PMT (with and without shock model) cutoff we have identified eligible. Then we have calculated eligible percentage from survey population. After that we have generalized it to whole country population.				

5.6 Conclusion and Policy Recommendation

A large segment of Pakistani society is highly vulnerable to different shocks and falls below the poverty line. BISP base line survey shows that, household face different types of shocks, i.e., individual level (idiosyncratic shocks) and the entire community (covariate) shocks. Thus, the nature of poverty in Pakistan is dynamic. There is possibility that households which were not eligible for BISP, may become eligible over the time due economic and climatic shocks. Similarly, there is a possibility that a household that entered in BISP at a certain level of welfare may not need assistance following a significant positive shock. We have simulated a shock adjusted targeting method which capture the dynamic nature of poverty.

Targeting performance of shock adjusted model is much better in terms of coverage of bottom 20percent population as compared to targeting model without shocks. Overall targeting performance of shock adjusted model is increase to 67 percent as compared to 60 targeting performance of without shock model. Coverage of bottom 20 percent from urban areas is decreased to 42percent as compared to 55 percent previously. Urban areas were given over coverage in previous model adopted by BISP based on HIES 2013-14. This motivates us to suggest policy makers to adopt shock adjusted targeting method which is not only dynamic itself but also capture dynamic nature of poverty.

References

Abegaz, T., et al. (2014). "Effects of excessive speeding and falling asleep while driving on crash injury severity in Ethiopia: A generalized ordered logit model analysis." *Accident Analysis & Prevention* 71: 15-21.

Abid, M., et al. (2020). "Ex-ante and ex-post coping strategies for climatic shocks and adaptation determinants in rural Malawi." *Climate Risk Management* 27: 100200.

Agwu, J. and A. Okhimamhe (2009). Gender and climate change in Nigeria: A study of four communities in north-central and south-eastern Nigeria. Heinrich Böll Stiftung, Nigeria, Lagos.

Ahmad, D. and M. Afzal (2021). "Flood hazards, human displacement and food insecurity in rural riverine areas of Punjab, Pakistan: policy implications." *Environmental Science and Pollution Research* 28(8): 10125-10139.

Ahmad, M. and U. Farooq (2010). "The state of food security in Pakistan: Future challenges and coping strategies." *The Pakistan Development Review*: 903-923.

Ahmad, M., et al. (2016). "Impact of farm households' adaptations to climate change on food security: Evidence from different agro-ecologies of Pakistan." *The Pakistan Development Review*: 561-588.

Ahmed, A. U. and H. E. Bouis (2002). "Weighing what’s practical: proxy means tests for targeting food subsidies in Egypt." *Food Policy* 27(5-6): 519-540.

Akter, S. and S. A. Basher (2014). "The impacts of food price and income shocks on household food security and economic well-being: Evidence from rural Bangladesh." *Global Environmental Change* 25: 150-162.

Alamgir, M., et al. (2021). "Farm income, inequality, and poverty among farm families of a flood-prone area in Bangladesh: climate change vulnerability assessment." *GeoJournal* 86(6): 2861-2885.

Alatas, V., et al. (2013). Ordeal mechanisms in targeting: Theory and evidence from a field experiment in Indonesia, National Bureau of Economic Research.

Ali, A. (2018). "Impact of climate-change risk-coping strategies on livestock productivity and household welfare: Empirical evidence from Pakistan." *Heliyon* 4(10): e00797.

Ali, A. and O. Erenstein (2017). "Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan." *Climate Risk Management* 16: 183-194.

Ali, A. and D. B. Rahut (2020). "Localized floods, poverty and food security: empirical evidence from rural Pakistan." *Hydrology* **7**(1): 2.

Ali, L., et al. (2020). "Financial Fragility of Pakistani Household." *Journal of Family and Economic Issues* 41(3): 572-590.

Ambler, K. and A. De Brauw (2019). *Household labor supply and social protection: Evidence from Pakistan's BISP cash transfer program*, Intl Food Policy Res Inst.

Anderson, R., et al. (2020). "Climate change and the need for agricultural adaptation." *Current opinion in plant biology* 56: 197-202.

Angula, M. N. (2010). Gender and climate change: Namibia case study, Heinrich Böll Stiftung.

Ansah, I. G. K., et al. (2021). "Shock interactions, coping strategy choices and household food security." *Climate and Development* 13(5): 414-426.

Arif, G. M. and F. Bilquees (2007). "Chronic and transitory poverty in Pakistan: Evidence from a longitudinal household survey." *The Pakistan Development Review*: 111-127.

Arif, G. M. and S. Farooq (2014). "Rural poverty dynamics in Pakistan: Evidence from three waves of the panel survey." *The Pakistan Development Review* 53(2): 71-98.

Arif, G. M., et al. (2011). "The persistence and transition of rural poverty in Pakistan: 1998-2004." *Working Papers & Research Reports* 2011.

Asfaw, S., et al. (2017). "Cash transfer programmes, weather shocks and household welfare: evidence from a randomised experiment in Zambia." *Journal of Development Effectiveness* 9(4): 419-442.

Asghar, N. and T. A. Naveed (2015). "Pass-through of world oil prices to inflation: A time series analysis of Pakistan." *Pakistan Economic and Social Review*: 269-284.

Ashraf, M. and J. K. Routray (2013). "Perception and understanding of drought and coping strategies of farming households in North-West Balochistan." *International Journal of Disaster Risk Reduction* 5: 49-60.

Azeem, M. M., et al. (2016). "Living on the edge: Household vulnerability to food-insecurity in the Punjab, Pakistan." *Food Policy* 64: 1-13.

Azeem, M. M., et al. (2019). "Do social protection transfers reduce poverty and vulnerability to poverty in Pakistan? Household level evidence from Punjab." *The Journal of Development Studies* 55(8): 1757-1783.

Azevedo, V. and M. Robles (2013). "Multidimensional targeting: Identifying beneficiaries of conditional cash transfer programs." *Social Indicators Research* 112(2): 447-475.

Baez, J. E., et al. (2015). "Gone with the storm: Rainfall shocks and household well-being in Guatemala." World Bank Policy Research Working Paper(7177).

Bakkensen, L. and L. Barrage (2018). Climate shocks, cyclones, and economic growth: bridging the micro-macro gap, National Bureau of Economic Research.

Barrett, C. B., et al. (2001). "Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications." *Food Policy* 26(4): 315-331.

Bhalla, G., et al. (2018). "The effect of cash transfers and household vulnerability on food security in Zimbabwe." *Food Policy* 74: 82-99.

Brown, C., et al. (2018). "A poor means test? Econometric targeting in Africa." *Journal of Development Economics* 134: 109-124.

Bukhari, A. H. and S. U. Khan (2008). "A small open economy DSGE model for Pakistan." *The Pakistan Development Review*: 963-1008.

Caminada, K. and K. Goudswaard (2005). "Are public and private social expenditures complementary?" *International Advances in Economic Research* 11(2): 175-189.

Caminada, K., et al. (2012). "Social income transfers and poverty: A cross-country analysis for OECD countries." *International Journal of Social Welfare* 21(2): 115-126.

Carter, M. R. and C. B. Barrett (2006). "The economics of poverty traps and persistent poverty: An asset-based approach." *The Journal of Development Studies* 42(2): 178-199.

Castañeda, T., et al. (2005). "Designing and implementing household targeting systems: lessons from Latin America and the United States." *World Bank Social Protection Discussion Paper Series* 526.

Catalano, M., et al. (2020). "Climate-change adaptation: The role of fiscal policy." *Resource and Energy Economics* 59: 101111.

Cheema, I., et al. (2014). Benazir income support programme, Oxford Policy Management Limited, Oxford, United Kingdom.

Cho, Y., et al. (2021). "Mitigating the Impact of COVID-19 on the Welfare of Low Income Households in the Philippines: The Role of Social Protection." *COVID-19 Low Income HOPE Survey Note* (1).

Coady, D., et al. (2004). "Targeting of transfers in developing countries: Review of lessons and experience."

Conning, J. and M. Kevane (2002). "Community-based targeting mechanisms for social safety nets: A critical review." *World Development* 30(3): 375-394.

Deaton, A. (1989). Saving and liquidity constraints, national bureau of economic research Cambridge, Mass., USA.

Deen, S. (2015). "Pakistan 2010 floods. Policy gaps in disaster preparedness and response." *International Journal of Disaster Risk Reduction* 12: 341-349.

Dercon, S. and P. Krishnan (2000). "Vulnerability, seasonality and poverty in Ethiopia." *The Journal of Development Studies* 36(6): 25-53.

Devereux, S., et al. (2017). "The targeting effectiveness of social transfers." *Journal of Development Effectiveness* 9(2): 162-211.

Deyshappriya, N. (2020). "Economic Impacts of COVID-19 Macro and Microeconomics Evidences from Sri Lanka." *Economic Impacts of COVID-19 Macro and Microeconomics Evidences from Sri Lanka* (May 10, 2020).

Dhanaraj, S. (2016). "Economic vulnerability to health shocks and coping strategies: evidence from Andhra Pradesh, India." *Health Policy and Planning* 31(6): 749-758.

Eckstein, D., et al. (2019). "Global climate risk index 2020." *Bonn: Germanwatch*.

Eluru, N. and S. Yasmin (2015). "A note on generalized ordered outcome models." *Analytic Methods in Accident Research* 8: 1-6.

Farooq, S. (2014). "Effectiveness of cash transfer programmes for household welfare in Pakistan: The case of the Benazir Income Support Programme." *The Pakistan Development Review* 53(2): 145-174.

Ferraro, P. J. and R. Simorangkir (2020). "Conditional cash transfers to alleviate poverty also reduced deforestation in Indonesia." *Science Advances* 6(24): eaaz1298.

Firdaus, R. R., et al. (2019). "Does climate change only affect food availability? What else matters?" *Cogent Food & Agriculture* 5(1): 1707607.

Gazdar, H. (2011). "Social protection in Pakistan: in the midst of a paradigm shift?" *Economic and Political Weekly*: 59-66.

Gazdar, H. and H. B. Mallah (2013). "Inflation and food security in Pakistan: Impact and coping strategies." *IDS Bulletin* 44(3): 31-37.

Glewwe, P. and O. Kanaan (1989). Targeting assistance to the poor: A multivariate approach using household survey data.

Gregory, P. J., et al. (2005). "Climate change and food security." *Philosophical Transactions of the Royal Society B: Biological Sciences* 360(1463): 2139-2148.

Grosh, M. and J. L. Baker (1995). "Proxy means tests for targeting social programs." *Living Standards Measurement Study Working Paper* 118: 1-49.

Grosh, M., et al. (2008). *For Protection and Promotion: The Design and Implementation of Effective Safety Nets,* World Bank Publications.

Grosh, M. and E. Glinskaya (1997). "Proxy means testing and social assistance in Armenia." *Draft. Development Economics Research Group, World Bank, Washington, DC.*

Grosh, M. E. (1994). *Administering Targeted Social Programs in Latin America: From Platitudes to Practice*, World Bank Publications.

Halaskova, R. and P. Bednář (2020). "Relationship of social protection expenditures and socio-economic indicators: A panel data analysis of the EU countries." *Montenegrin Journal of Economics.*

Hallegatte, S., et al. (2018). "Poverty and climate change: Introduction." *Environment and Development Economics* 23(3): 217-233.

Hallegatte, S. and J. Rozenberg (2017). "Climate change through a poverty lens." *Nature Climate Change* 7(4): 250-256.

Handa, S., et al. (2020). "The Impact of a Large-Scale Poverty-Targeted Cash Transfer Program on Intertemporal Choice." *Economic Development and Cultural Change* 69(1): 485-512.

Hanif, M. N. (2012). "A note on food inflation in Pakistan." *Pakistan Economic and Social Review*: 183-206.

Haq, R. (2015). "Shocks as a source of vulnerability: An empirical investigation from Pakistan." *The Pakistan Development Review*: 245-272.

Haseeb, M. and K. Vyborny (2016). Imposing institutions: Evidence from cash transfer reform in Pakistan, Centre for the Study of African Economies, University of Oxford.

Hayes, K. and B. Poland (2018). "Addressing mental health in a changing climate: Incorporating mental health indicators into climate change and health vulnerability and adaptation assessments." *International Journal of Environmental Research and Public Health* 15(9): 1806.

Heltberg, R. and N. Lund (2009). "Shocks, coping, and outcomes for Pakistan's poor: health risks predominate." *The Journal of Development Studies* 45(6): 889-910.

Hoddinott, J. (2006). "Shocks and their consequences across and within households in rural Zimbabwe." *The Journal of Development Studies* 42(2): 301-321.

Hoddinott, J. and B. Kinsey (2000). Adult health in the time of drought.

Hossain, M. and M. K. Mujeri (2020). "Inflation and Household Welfare: Evidence from Bangladesh." *Bangladesh's Macroeconomic Policy: Trends, Determinants and Impact*.

Hulme, D. and A. Shepherd (2003). "Conceptualizing chronic poverty." *World Development* 31(3): 403-423.

Iqbal, N. and S. Nawaz (2017). "Targeting efficiency and effectiveness of national cash transfers program: Lessons from BISP, Pakistan." *Economic Challenges Facing Pakistan in the Regional and Global Environment* 19: 337-357.

Islam, M. S. and E. Kieu (2020). "Tackling regional climate change impacts and food security issues: A critical analysis across ASEAN, PIF, and SAARC." *Sustainability* 12(3): 883.

Jafar, M., et al. (2020). "We Are All Made Poor Here: Adequacy of Social Protection Programs in Pakistan." *Journal of the Research Society of Pakistan* 57(1): 195.

Jalal, A. (2017). "The Targeting Performance and Short-Term Welfare Effects of Female Income Support Programs: Evidence from Pakistan." Unpublished Thesis, Department of Economics, Yale University, available at https://economics. yale. edu/sites/default/files/files/Undergraduate/Nominated% 20Senior% 20Essays/2016-17/Amen_Jalal Senior% 20Essay. pdf.

Jungehülsing, J. (2010). Women who go, women who stay: Reactions to climate change. A case study on migration and gender in Chiapas. Heinrich Böll Stiftung, Mexico, Central America and the Caribbean.

Khalid, M., et al. (2007). "The fiscal reaction function and the transmission mechanism for Pakistan." *The Pakistan Development Review*: 435-447.

Khan, S. N. and S. Qutub (2010). "The Benazir Income Support programme and the Zakat programme: A political economy analysis of gender." *London: Overseas Development Institute (ODI)*: 1-42.

Khayyam, U. and S. Noureen (2020). "Assessing the adverse effects of flooding for the livelihood of the poor and the level of external response: a case study of Hazara Division, Pakistan." *Environmental Science and Pollution Research* 27(16): 19638-19649.

Kidd, S. and E. Wylde (2017). "B. Gelders and D. Bailey-Athias."Exclusion by Design: An Assessment of the Effectiveness of the Proxy Means Test Poverty

Targeting Mechanism”. International Labour Office." *Social Protection Department (SOCPRO), Geneva.*

Kleve, S., et al. (2017). "Are low-to-middle-income households experiencing food insecurity in Victoria, Australia? An examination of the Victorian Population Health Survey, 2006–2009." *Australian Journal of Primary Health* 23(3): 249-256.

Kogo, B. K., et al. (2021). "Climate change and variability in Kenya: a review of impacts on agriculture and food security." *Environment, Development and Sustainability* 23(1): 23-43.

Kosec, K. and C. H. Mo (2017). "Aspirations and the role of social protection: Evidence from a natural disaster in rural Pakistan." *World Development* 97: 49-66.

Kurosaki, T. and H. U. Khan (2012). "Vulnerability of microfinance to strategic Default and covariate shocks: evidence from Pakistan." *The Developing Economies* 50(2): 81-115.

Lara Ibarra, G., et al. (2017). "Rental regulation and its consequences on measures of well-being in the Arab Republic of Egypt." *World Bank Policy Research Working Paper*(8152).

Lim, S. S. (2017). "In times of sickness: Intra-household labour substitution in rural Indonesian households." *The Journal of Development Studies* 53(6): 788-804.

Lokonon, B. O. K. (2019). "Farmers' vulnerability to climate shocks: insights from the Niger basin of Benin." *Climate and Development* 11(7): 585-596.

Marcoux, R., et al. (2018). "Evaluating temporal variability of exogenous variable impacts over 25 years: An application of scaled generalized ordered logit model for driver injury severity." *Analytic Methods in Accident Research* 20: 15-29.

Markhvida, M., et al. (2020). "Quantification of disaster impacts through household well-being losses." *Nature Sustainability* 3(7): 538-547.

Mitchell, T., et al. (2007). "'We know what we need': South Asian women speak out on climate change adaptation."

Mitra, S., et al. (2016). "Can households cope with health shocks in Vietnam?" *Health Economics* 25(7): 888-907.

Mustafa, G., et al. (2019). "Impact of Unconditional Cash Transfer on Child Nutrition in Pakistan: Evidence from Benazir Income Support Program (BISP)."

Nabi, A. A., et al. (2020). "Relationship between population growth, price level, poverty incidence, and carbon emissions in a panel of 98 countries." *Environmental Science and Pollution Research* 27: 31778-31792.

Narayan, A. and N. Yoshida (2005). "Proxy Means Tests for Targeting Welfare Benefits in Sri Lanka." Report No. SASPR–7, Washington, DC: World Bank, http://siteresources. worldbank. org/EXTSAREGTOPPOVRED/Resources/49344 0-1102216396155/572861-1102221461685/Proxy+ Means+ Test+ for+ Targeting+ Welfare+ Benefits. pdf, accessed February 5: 2009.

Nellemann, C., et al. (2011). "Women at the frontline of climate change: Gender risks and hopes." *A Rapid Response Assessment. United Nations Environment Programme, GRID-Arendal.*

Paavola, J. (2017). "Health impacts of climate change and health and social inequalities in the UK." *Environmental Health* 16(1): 61-68.

Patel, S. K., et al. (2020). "Traditional agricultural practices in India: an approach for environmental sustainability and food security." *Energy, Ecology and Environment* 5(4): 253-271.

Persaud, M. A. "CARIBBEAN COMMUNITY SECRETARIAT."

Reyes, R. R. (2002). "Gendering responses to El Niño in rural Peru." *Gender & Development* 10(2): 60-69.

Rustamovich, K. M. (2019). "The Impact of Economic Sanctions on Well-being of Vulnerable Populations of Target Countries." *International Journal on Economics, Finance and Sustainable Development* 1(1): 17-20.

Saeed, M. K. and M. A. Hayat (2020). "The Impact of Social Cash Transfers on Poverty in Pakistan-A Case Study of Benazir Income Support Programme."

Sakyi, D., et al. (2018). "Trade facilitation and social welfare in Africa." *Journal of African Trade* 5(1-2): 35-53.

Sardar, A., et al. (2021). "Does adoption of climate-smart agriculture (CSA) practices improve farmers' crop income? Assessing the determinants and its impacts in Punjab province, Pakistan." *Environment, Development and Sustainability* 23(7): 10119-10140.

Schnitzer, P. (2016). "How to Target Households in Adaptive Social Protection Systems?".

Sebastian, A. R., et al. (2018). "A proxy means test for Sri Lanka." *World Bank Policy Research Working Paper*(8605).

Serna, J. (2011). "Drought Assessment Northern Eastern Kenya (Wajir East, South and Mandera)." *Northern Eastern Kenya Drought Assessment Report*.

Sharif, I. (2009). *Building a targeting system for Bangladesh based on proxy means testing*, Citeseer.

Sher, A., et al. (2018). "Who is more Food Secure among Rural, Peri-urban and Urban Households in Pakistan? Results from a field survey in Punjab province."

Stoeffler, Q., et al. (2016). "Reaching the poor: Cash transfer program targeting in Cameroon." *World Development* 83: 244-263.

Tasos, S., et al. (2020). "Poverty Alleviation and Microfinance for the Economy of Pakistan: A Case Study of Khushhali Bank in Sargodha." *Economies* 8(3): 63.

Ullah, H., et al. (2018). "Perceptions of mountainous people on climate change, livelihood practices and climatic shocks: A case study of Swat District, Pakistan." *Urban Climate* 26: 244-257.

Ullah, S., et al. (2020). "Asymmetric effects of inflation instability and GDP growth volatility on environmental quality in Pakistan." *Environmental Science and Pollution Research* 27: 31892-31904.

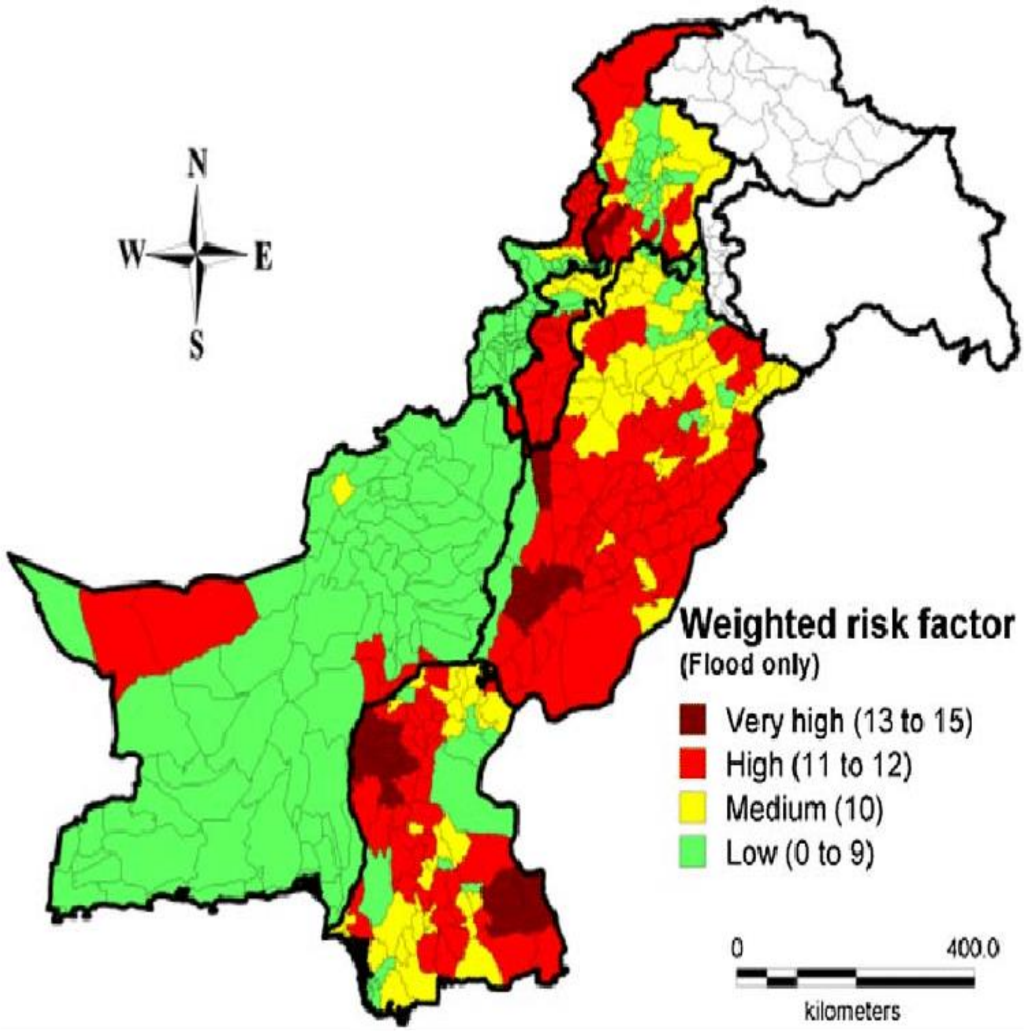
Van Epp, M. and B. Garside (2019). "Towards an evidence base on the value of social learning-oriented approaches in the context of climate change and food security." *Environmental Policy and Governance* 29(2): 118-131.

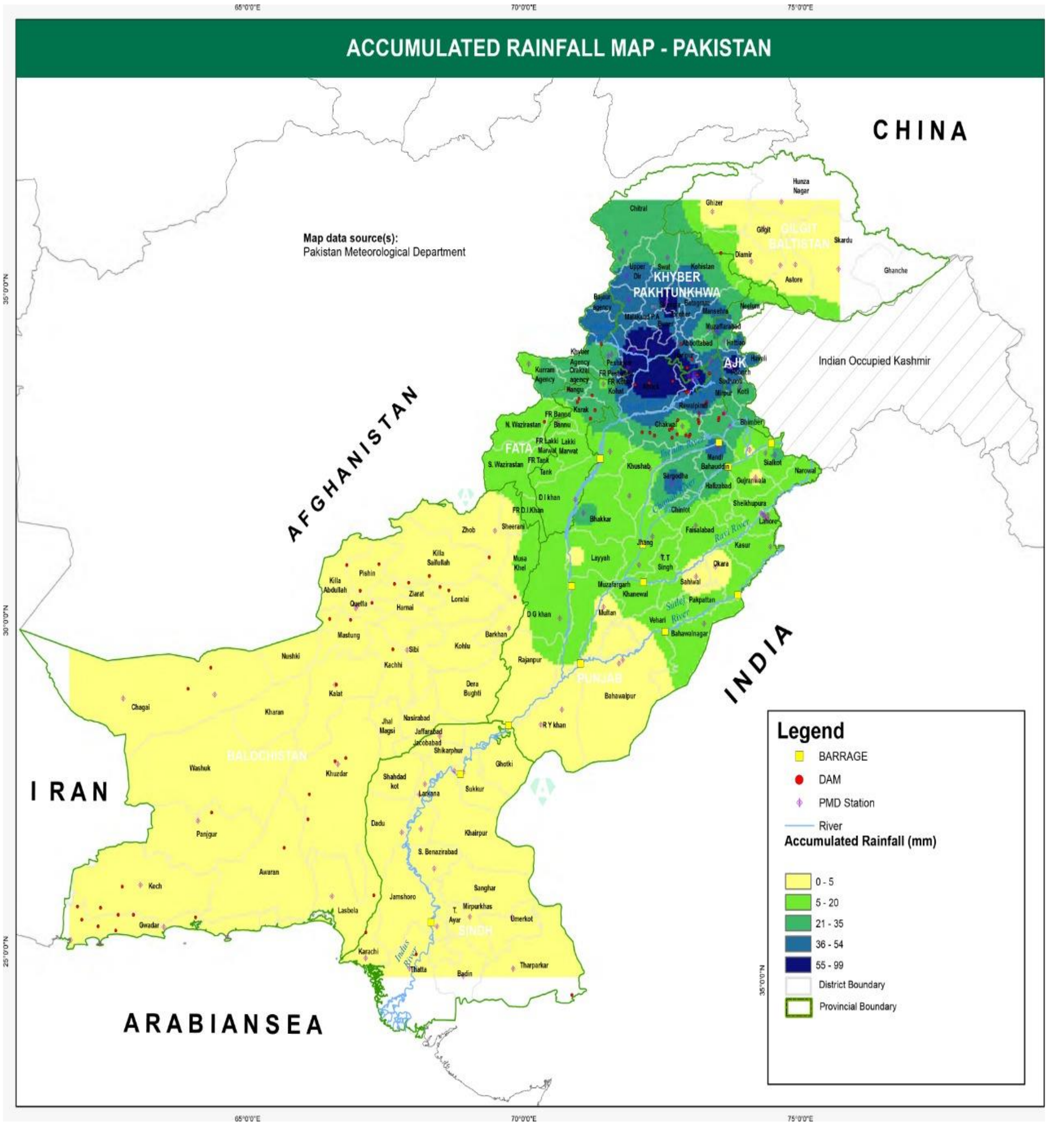
Venkataramanan, V., et al. (2019). "A systematic review of the human health and social well-being outcomes of green infrastructure for stormwater and flood management." *Journal of Environmental Management* 246: 868-880.

Watson, C., et al. (2017). Shock-responsive social protection systems research, Oxford.

Williams, R. (2016). "Understanding and interpreting generalized ordered logit models." *The Journal of Mathematical Sociology* 40(1): 7-20.

Appendices


N
W
E
S
Weighted risk factor
(Flood only)
Very high (13 to 15)
High (11 to 12)
Medium (10)
Low (0 to 9)
0
400.0
kilometers


ACCUMULATED RAINFALL MAP - PAKISTAN
CHINA
AFGHANISTAN
INDIA
IRAN
ARABIANSEA
Indian Occupied Kashmir
Map data source(s):
Pakistan Meteorological Department
KHYBER PAKHTUNKHWA
AJK
FATA
PUNJAB
BALOCHISTAN
SINDH
GILGIT BALTISTAN
Legend
BARRAGE
DAM
PMD Station
River
Accumulated Rainfall (mm)
0 - 5
5 - 20
21 - 35
36 - 54
55 - 99
District Boundary
Provincial Boundary

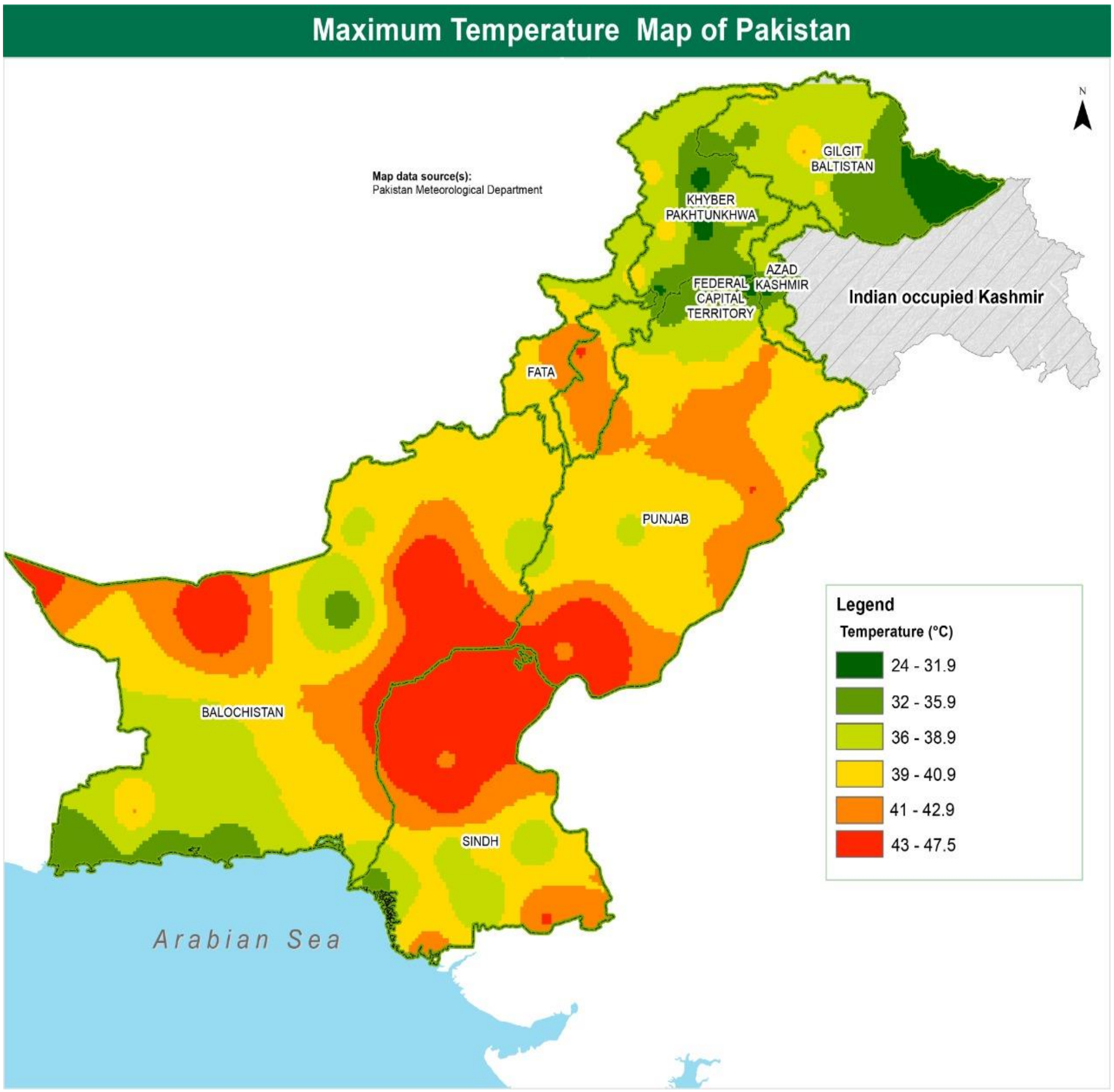

Maximum Temperature Map of Pakistan
Map data source(s):
Pakistan Meteorological Department
N
GILGIT
BALTISTAN
KHYBER
PAKHTUNKHWA
AZAD
KASHMIR
FEDERAL
CAPITAL
TERRITORY
Indian occupied Kashmir
FATA
PUNJAB
BALOCHISTAN
SINDH
Arabian Sea
Legend
Temperature (°C)
24 - 31.9
32 - 35.9
36 - 38.9
39 - 40.9
41 - 42.9
43 - 47.5

Table 3.1M: Correlation Matrix

	Avrg_Fl	flood_~k	precip~g	Precip~k	temp_avg	temper~k	head_~re	head_s~r	head_p~e	hhsizeM
Avrg_Fl	1.0000									
flood_shock	-0.2572	1.0000								
precip_avg	-0.0535	0.1441	1.0000							
Precipitat~k	-0.0759	-0.0701	-0.4762	1.0000						
temp_avg	-0.0800	-0.1582	-0.8367	0.3892	1.0000					
temperatur~k	0.0847	0.1649	0.8236	-0.4041	-0.9981	1.0000				
head_agric~e	0.1051	-0.0199	-0.0406	-0.0057	0.0433	-0.0394	1.0000			
head_self_~r	-0.0130	-0.0330	0.0411	-0.0402	-0.0167	0.0140	-0.2088	1.0000		
head_paid_~e	-0.0292	0.0238	-0.1243	0.1076	0.0803	-0.0795	-0.4384	-0.4199	1.0000	
hhsizeM	0.0344	0.0390	0.0792	0.0400	-0.1349	0.1428	0.0977	0.0429	-0.0913	1.0000
head_age	-0.0450	0.0133	0.0974	-0.0775	-0.0861	0.0856	0.0960	-0.0470	-0.2622	0.2153
dependency~o	0.0408	0.0024	0.0583	-0.0192	-0.0607	0.0637	-0.0056	-0.0216	-0.0521	0.1613
head_gender	0.0221	-0.0064	-0.1522	0.1330	0.1155	-0.1132	0.1122	0.1181	0.1919	0.1603
head_married	0.0197	0.0055	-0.0106	0.0032	-0.0000	0.0016	0.0123	0.0152	-0.0222	0.0931

Appendix-3.7A: Impact of Covariate Shocks on Log Expenditures (Using shock one by one)			
Dependent: Log Expenditures	(1)	(2)	(3)
	Flood Shock	Rainfall Shock	Temperature
Average Flood	-0.183***		
	(0.0583)		
Flood Shock	0.0204**		
	(0.01000)		
Rainfall		0.0644***	
		(0.00477)	
Rainfall Shock		-0.00637***	
		(0.00517)	
Temperature Average			-0.0986***
			(0.00993)
Temperature Shock			-0.0874***
			(0.00996)
Head Agriculture	0.0165*	0.0178*	0.0170*
	(0.00965)	(0.00960)	(0.00962)
Self-employed	-0.0187*	-0.0186*	-0.0199*
	(0.0106)	(0.0106)	(0.0106)
Paid Employee	-0.118***	-0.117***	-0.119***
	(0.00924)	(0.00917)	(0.00918)
Household Size	-0.0531***	-0.0534***	-0.0528***
	(0.00119)	(0.00119)	(0.00120)
Head age	0.00319***	0.00306***	0.00307***
	(0.000227)	(0.000226)	(0.000226)
Dependency Ratio	-0.0917***	-0.0912***	-0.0912***
	(0.00368)	(0.00367)	(0.00366)
Head Gender	-0.0875***	-0.0747***	-0.0786***
	(0.0114)	(0.0113)	(0.0114)
Head Married	-0.141***	-0.137***	-0.138***
	(0.0202)	(0.0199)	(0.0199)
Flush Toilet	0.233***	0.227***	0.219***
	(0.00594)	(0.00591)	(0.00597)

Rural	-0.245***	-0.246***	-0.245***
	(0.00646)	(0.00636)	(0.00638)
Sindh	-0.0598***	0.0307***	-0.0342***
	(0.00689)	(0.00802)	(0.00695)
KPK	-0.0137*	-0.163***	-0.135***
	(0.00727)	(0.0146)	(0.0104)
Balochistan	-0.0876***	-0.0123	-0.0669***
	(0.00874)	(0.00912)	(0.00947)
Constant	9.234***	9.098***	9.624***
	(0.0244)	(0.0251)	(0.0342)
In this table three different models are estimated through OLS. Here we have estimated the impact of shocks one by one. Almost results are same as they are jointly estimated. Flood, rainfall and temperature shocks have significant negative impact.			

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

Table-3.7A Impact of Flood Shocks on Household's Well-being: OLS Estimation (HIES 2018-19)

	(1)	(2)	(3)	(4)	(5)
Variables	Log PAE Expenditure	Log PAE Calorie	Log HH Income	Log Food Share	Log Non-food Share
Average Flood	-0.272***	-0.360***	-0.733***	0.406***	-0.302***
	(0.0582)	(0.0410)	(0.0931)	(0.0399)	(0.0333)
Flood Shock	-0.0240**	-0.0165***	-0.0450***	0.0191***	-0.0194***
	(0.0102)	(0.00607)	(0.0167)	(0.00722)	(0.00627)
Average Rainfall	0.0700***	-0.00511**	0.114***	-0.0275***	0.0125***
	(0.00377)	(0.00236)	(0.00639)	(0.00257)	(0.00183)
Head Agriculture	0.0200**	0.0652***	0.156***	0.0707***	-0.0505***
	(0.00960)	(0.00613)	(0.0193)	(0.00626)	(0.00469)
Head Self-employed	-0.0176*	0.00513	0.341***	0.0192***	-0.00940**
	(0.0106)	(0.00656)	(0.0188)	(0.00677)	(0.00456)
Head Paid Employee	-0.117***	-0.0426***	0.246***	0.0377***	-0.0263***
	(0.00916)	(0.00569)	(0.0176)	(0.00589)	(0.00405)
Household Size	-0.0532***	-0.0297***	0.0860***	0.00572***	-0.00308***
	(0.00119)	(0.000715)	(0.00165)	(0.000580)	(0.000444)
Head age	0.00303***	0.00307***	0.00767***	-0.000786***	0.000245**
	(0.000226)	(0.000148)	(0.000394)	(0.000145)	(0.000108)
Dependency Ratio	-0.0909***	-0.0779***	-0.191***	0.0284***	-0.0206***
	(0.00366)	(0.00249)	(0.00661)	(0.00231)	(0.00176)
Head Gender	-0.0750***	-0.0400***	0.624***	0.0149**	-0.0100**
	(0.0113)	(0.00703)	(0.0285)	(0.00724)	(0.00492)
Head Married	-0.135***	-0.137***	-0.0198	-0.00128	0.0130
	(0.0198)	(0.0138)	(0.0312)	(0.0131)	(0.00974)
Flush Toilet	0.226***	0.0512***	0.294***	-0.115***	0.110***
	(0.00591)	(0.00419)	(0.00989)	(0.00410)	(0.00362)
Region (1=rural, 0=urban)	-0.242***	0.00637	-0.316***	0.140***	-0.0919***
	(0.00641)	(0.00395)	(0.00953)	(0.00417)	(0.00285)
Sindh	0.0384***	0.0403***	0.121***	0.0548***	-0.0547***
	(0.00830)	(0.00520)	(0.0129)	(0.00545)	(0.00420)
KPK	-0.176***	0.141***	-0.386***	0.103***	-0.0567***
	(0.0118)	(0.00747)	(0.0195)	(0.00812)	(0.00553)
Balochistan	-0.0126	0.0563***	0.121***	0.0596***	-0.0541***
	(0.00933)	(0.00643)	(0.0141)	(0.00649)	(0.00554)

Constant	9.100***	7.958***	10.83***	3.665***	4.041***
	(0.0248)	(0.0169)	(0.0521)	(0.0165)	(0.0124)
Observations	24,663	24,663	23,072	24,663	24,663
R-squared	0.369	0.227	0.372	0.205	0.216
Here we have reported the impact of flood shock only on five different households' well-being indicators. Flood shock has significant negative impact on all five well-being indicators.					

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

Appendix 3.7B: Impact of Shocks on Insecurity Food Insecure=1,0 otherwise			
Log of Calorie Intakes	(1)	(2)	(3)
Variables	Flood Shock	Rainfall Shock	Temperature Shock
Average Flood	-0.366***		
	(0.0409)		
Flood Shock	0.0197***		
	(0.00600)		
Rainfall		0.00717**	
		(0.00301)	
Rainfall Shock		0.0245***	
		(0.00332)	
Temperature Average			0.0311***
			(0.00663)
Temperature Shock			0.0297***
			(0.00667)
Head Agriculture	0.0655***	0.0636***	0.0623***
	(0.00613)	(0.00613)	(0.00615)
Self-employed	0.00521	0.00487	0.00424
	(0.00656)	(0.00656)	(0.00657)
Paid Employee	-0.0425***	-0.0427***	-0.0425***
	(0.00569)	(0.00569)	(0.00570)
Household Size	-0.0298***	-0.0300***	-0.0302***
	(0.000715)	(0.000715)	(0.000719)
Head age	0.00306***	0.00313***	0.00312***
	(0.000148)	(0.000148)	(0.000148)
Dependency Ratio	-0.0779***	-0.0781***	-0.0784***
	(0.00249)	(0.00249)	(0.00249)
Head Gender	-0.0391***	-0.0416***	-0.0398***
	(0.00701)	(0.00704)	(0.00704)
Head Married	-0.137***	-0.138***	-0.139***
	(0.0138)	(0.0138)	(0.0138)
Flush Toilet	0.0507***	0.0528***	0.0554***
	(0.00418)	(0.00418)	(0.00423)
Rural	0.00656*	0.00299	0.00125
	(0.00395)	(0.00393)	(0.00394)
Sindh	0.0475***	0.0280***	0.0363***
	(0.00433)	(0.00507)	(0.00441)
KPK	0.129***	0.103***	0.148***
	(0.00455)	(0.00928)	(0.00652)
Balochistan	0.0617***	0.0620***	0.0574***
	(0.00612)	(0.00634)	(0.00677)
Constant	7.948***	7.991***	7.885***
	(0.0165)	(0.0172)	(0.0226)
Binary variable of food insecurity indicated that 1 is assigned if household found having daily calorie intake is below 2350 kilo calories per adult, 0 is assigned otherwise. Hence the positive sign of shock on outcome variable will indicate the adverse impact of shocks. Here we have estimated impact of covariate shocks one by one on food insecurity status. Results indicate the negative impact of shocks on food insecurity status.			

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

Table-3.7B: Impact of Climatic Shocks on Households' Wellbeing: OLS Estimation					
	(1)	(2)	(3)	(4)	(5)
Variables	Log PAE Expenditure	Log PAE Calorie Intake	Log HH Income	Log Food Share	Log Non-food Share
Average Rainfall	0.0411***	0.0165***	0.0664***	-0.0434***	0.0253***
	(0.00574)	(0.00382)	(0.00951)	(0.00394)	(0.00290)
Rainfall Shock	-0.0279***	0.0381***	-0.0592***	0.00720*	-0.00613**
	(0.00584)	(0.00376)	(0.00979)	(0.00387)	(0.00275)
Average Temperature	-0.113***	0.0655***	-0.179***	0.0628***	-0.0386***
	(0.0110)	(0.00740)	(0.0173)	(0.00765)	(0.00586)
Temperature Shock	-0.111***	0.0658***	-0.178***	0.0704***	-0.0447***
	(0.0111)	(0.00745)	(0.0175)	(0.00776)	(0.00592)
Head Agriculture	0.0183*	0.0632***	0.153***	0.0725***	-0.0519***
	(0.00959)	(0.00613)	(0.0193)	(0.00624)	(0.00467)
Head Self-employed	-0.0202*	0.00580	0.337***	0.0210***	-0.0106**
	(0.0105)	(0.00656)	(0.0187)	(0.00676)	(0.00455)
Head Paid Employee	-0.118***	-0.0419***	0.245***	0.0384***	-0.0267***
	(0.00915)	(0.00569)	(0.0176)	(0.00588)	(0.00404)
Household Size	-0.0526***	-0.0304***	0.0868***	0.00546***	-0.00292***
	(0.00119)	(0.000719)	(0.00165)	(0.000579)	(0.000443)
Head age	0.00300***	0.00316***	0.00768***	-0.000830***	0.000280***
	(0.000226)	(0.000147)	(0.000394)	(0.000145)	(0.000108)
Dependency Ratio	-0.0908***	-0.0784***	-0.192***	0.0283***	-0.0205***
	(0.00366)	(0.00249)	(0.00662)	(0.00231)	(0.00176)
Head Gender	-0.0738***	-0.0418***	0.629***	0.0169**	-0.0115**
	(0.0113)	(0.00704)	(0.0286)	(0.00724)	(0.00492)
Head Married	-0.135***	-0.140***	-0.0207	-0.00151	0.0130
	(0.0198)	(0.0138)	(0.0312)	(0.0131)	(0.00976)
Flush Toilet	0.218***	0.0581***	0.283***	-0.113***	0.110***
	(0.00597)	(0.00423)	(0.00996)	(0.00412)	(0.00365)
Region (1=rural, 0=urban)	-0.242***	0.000477	-0.319***	0.140***	-0.0926***
	(0.00636)	(0.00394)	(0.00946)	(0.00414)	(0.00284)
Sindh	0.0258***	0.0278***	0.1000***	0.0512***	-0.0514***
	(0.00816)	(0.00524)	(0.0129)	(0.00535)	(0.00429)
KPK	-0.155***	0.0950***	-0.325***	0.0987***	-0.0498***
	(0.0148)	(0.00939)	(0.0246)	(0.00994)	(0.00711)
Balochistan	0.0162	0.0371***	0.184***	-0.00988	-0.00394
	(0.0112)	(0.00791)	(0.0179)	(0.00809)	(0.00649)
Constant	9.242***	7.962***	10.95***	3.878***	3.861***
	(0.0439)	(0.0312)	(0.0782)	(0.0306)	(0.0241)
Observations	24,663	24,663	23,072	24,663	24,663
R-squared	0.371	0.229	0.373	0.208	0.219
In this table we have reported the impact of climatic shocks on five different indicators of households' well-being. Both rainfall and temperature shocks have significant negative impact on all indicators of households' well-being.					

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

Appendix-3.8A: Impact of Shock on Poverty Status (poor=1, 0=non-poor); Logit Estimation			
Poor=1, non-poor=0	(1)	(2)	(3)
Variables	Flood Shock	Rainfall Shock	Temperature Shock
Average Flood	-0.704		
	(0.447)		
Flood Shock	0.0443		
	(0.0704)		
Rainfall		-0.294***	
		(0.0364)	
Rainfall Shock		0.0710*	
		(0.0402)	
Temperature Average			0.444***
			(0.0744)
Temperature Shock			0.371***
			(0.0748)
Head Agriculture	-0.523***	-0.531***	-0.552***
	(0.0738)	(0.0740)	(0.0742)
Self-employed	-0.184**	-0.186**	-0.181**
	(0.0794)	(0.0797)	(0.0796)
Paid Employee	0.319***	0.320***	0.324***
	(0.0666)	(0.0668)	(0.0668)
Household Size	0.224***	0.225***	0.224***
	(0.00625)	(0.00625)	(0.00628)
Head age	-0.0126***	-0.0118***	-0.0118***
	(0.00163)	(0.00163)	(0.00163)
Dependency Ratio	0.516***	0.517***	0.516***
	(0.0229)	(0.0230)	(0.0230)
Head Gender	0.485***	0.423***	0.421***
	(0.0905)	(0.0909)	(0.0908)
Head Married	0.340**	0.326*	0.327*
	(0.167)	(0.168)	(0.167)
Flush Toilet	-1.183***	-1.157***	-1.129***
	(0.0445)	(0.0445)	(0.0449)
Rural	0.829***	0.827***	0.816***
	(0.0497)	(0.0496)	(0.0495)
Sindh	0.292***	-0.124**	0.0889*
	(0.0502)	(0.0591)	(0.0514)
KPK	-0.0456	0.689***	0.706***
	(0.0542)	(0.111)	(0.0764)
Balochistan	0.199***	-0.0561	0.229***
	(0.0647)	(0.0680)	(0.0728)
Constant	-3.757***	-3.183***	-6.273***
	(0.198)	(0.209)	(0.277)
In this table we have reported the impacts of covariate shocks one by one on the poverty status of household. Hence the positive sign of shock on outcome variable will indicate the adverse impact of shocks.			

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

Appendix-3.8B: Shocks and Food Insecurity Status (1=food insecure, 0=food secure): Logit Estimation			
Food insecurity Status	(1)	(2)	(3)
Variables	Flood Shock	Rainfall Shock	Temperature Shock
Average Flood	2.210***		
	(0.365)		
Flood Shock	0.149**		
	(0.0632)		
Rainfall		-0.0428*	
		(0.0260)	
Rainfall Shock		0.169***	
		(0.0278)	
Temperature Average			-0.240***
			(0.0590)
Temperature Shock			0.228***
			(0.0594)
Head Agriculture	-0.535***	-0.524***	-0.516***
	(0.0538)	(0.0537)	(0.0537)
Self-employed	-0.0667	-0.0651	-0.0606
	(0.0546)	(0.0546)	(0.0546)
Paid Employee	0.248***	0.248***	0.246***
	(0.0471)	(0.0471)	(0.0471)
Household Size	0.260***	0.261***	0.262***
	(0.00612)	(0.00612)	(0.00613)
Head age	-0.0215***	-0.0220***	-0.0219***
	(0.00121)	(0.00121)	(0.00121)
Dependency Ratio	0.566***	0.567***	0.570***
	(0.0206)	(0.0206)	(0.0206)
Head Gender	0.206***	0.224***	0.214***
	(0.0572)	(0.0573)	(0.0573)
Head Married	0.658***	0.667***	0.672***
	(0.101)	(0.101)	(0.101)
Flush Toilet	-0.335***	-0.348***	-0.371***
	(0.0396)	(0.0396)	(0.0400)
Rural	-0.0599*	-0.0376	-0.0261
	(0.0336)	(0.0334)	(0.0335)
Sindh	-0.299***	-0.163***	-0.224***
	(0.0379)	(0.0471)	(0.0387)
KPK	-0.919***	-0.750***	-1.076***
	(0.0414)	(0.0780)	(0.0576)
Balochistan	-0.455***	-0.438***	-0.410***
	(0.0572)	(0.0607)	(0.0623)
Constant	-1.157***	-1.470***	-0.626***
	(0.126)	(0.135)	(0.184)
In this table we have reported the impacts of different shocks separately on food insecurity status of household. Positive sign is indicating adverse impact of shocks.			

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

Appendix-3.9B: Impact of Shocks on Log Expenditures: Quantile Regression			
Log Expenditures	(1)	(2)	(3)
Variables	Flood Shock	Rainfall Shock	Temperature Shock
Average Flood	0.00667		
	(0.0702)		
Flood Shock	-0.0279**		
	(0.0123)		
Rainfall		0.0611***	
		(0.00510)	
Rainfall Shock		-0.0152***	
		(0.00545)	
Temperature Average			-0.0855***
			(0.0113)
Temperature Shock			-0.0744***
			(0.00567)
Head Agriculture	0.0301***	0.0324***	0.0315***
	(0.0105)	(0.0105)	(0.0103)
Self-employed	0.000926	0.00192	-0.00103
	(0.0108)	(0.0107)	(0.0105)
Paid Employee	-0.110***	-0.109***	-0.112***
	(0.00933)	(0.00926)	(0.00909)
Household Size	-0.0521***	-0.0522***	-0.0519***
	(0.000957)	(0.000949)	(0.000935)
Head age	0.00248***	0.00241***	0.00242***
	(0.000238)	(0.000236)	(0.000232)
Dependency Ratio	-0.0883***	-0.0872***	-0.0854***
	(0.00375)	(0.00372)	(0.00365)
Head Gender	-0.0836***	-0.0774***	-0.0774***
	(0.0114)	(0.0113)	(0.0111)
Head Married	-0.0958***	-0.0958***	-0.0954***
	(0.0198)	(0.0197)	(0.0193)
Flush Toilet	0.216***	0.210***	0.201***
	(0.00767)	(0.00761)	(0.00753)
Rural	-0.224***	-0.224***	-0.222***
	(0.00667)	(0.00657)	(0.00647)
Sindh	-0.0629***	0.0334***	-0.0315***
	(0.00750)	(0.00920)	(0.00746)
KPK	-0.00801	-0.152***	-0.124***
	(0.00802)	(0.0153)	(0.0109)
Balochistan	-0.0671***	0.00588	-0.0518***
	(0.0110)	(0.0115)	(0.0118)
Constant	9.156***	9.015***	9.535***
	(0.0248)	(0.0263)	(0.0353)
In this table impact of shocks (single shock models) on log of expenditure are reported. Significant negative impacts of shocks on log of expenditure are reported.			

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

Table-3.11A: Generalized Ordered Logit Model on Shocks and Calorie Intakes Five Quantiles								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reference	*GoLogit*	*Odds ratio*	*GoLogit*	*Odds ratio*	*GoLogit*	*Odds ratio*	*GoLogit*	*Odds ratio*
Fifth (Highest)	**Lowest Quantile (20)**		**Second Quantile (40)**		**Third Quantile (60)**		**Fourth Quantile (80)**	
Average Flood	-2.902***	0.0549***	-2.493***	0.0826***	-1.950***	0.142***	-2.315***	0.0987***
	(0.443)	(0.0243)	(0.384)	(0.0317)	(0.401)	(0.0571)	(0.516)	(0.0509)
Flood Shock	-0.258***	0.772***	-0.157***	0.854***	-0.120*	0.887*	-0.159*	0.853*
	(0.0700)	(0.0541)	(0.0589)	(0.0503)	(0.0616)	(0.0547)	(0.0841)	(0.0718)
Average Rainfall	0.0672	1.070	0.0685**	1.071**	0.110***	1.116***	0.0992**	1.104**
	(0.0439)	(0.0470)	(0.0343)	(0.0367)	(0.0336)	(0.0375)	(0.0407)	(0.0450)
Rainfall Shock	0.307***	1.359***	0.222***	1.248***	0.184***	1.202***	0.0947**	1.099**
	(0.0444)	(0.0604)	(0.0341)	(0.0425)	(0.0325)	(0.0391)	(0.0378)	(0.0416)
Avg. Temp.	0.624***	1.867***	0.394***	1.483***	0.402***	1.495***	0.242***	1.274***
	(0.0808)	(0.151)	(0.0665)	(0.0986)	(0.0670)	(0.100)	(0.0830)	(0.106)
Temp. Shock	0.673***	1.960***	0.417***	1.518***	0.412***	1.511***	0.235***	1.264***
	(0.0814)	(0.159)	(0.0670)	(0.102)	(0.0676)	(0.102)	(0.0838)	(0.106)
Head Agriculture	0.693***	2.000***	0.520***	1.682***	0.475***	1.608***	0.461***	1.586***
	(0.0707)	(0.141)	(0.0549)	(0.0923)	(0.0527)	(0.0847)	(0.0613)	(0.0972)
Head Self-employed	0.177***	1.194***	0.0564	1.058	0.0815	1.085	0.0293	1.030
	(0.0679)	(0.0811)	(0.0548)	(0.0580)	(0.0536)	(0.0582)	(0.0632)	(0.0651)
H. Paid Employee	-0.191***	0.826***	-0.271***	0.763***	-0.218***	0.804***	-0.218***	0.804***
	(0.0590)	(0.0488)	(0.0475)	(0.0362)	(0.0463)	(0.0372)	(0.0541)	(0.0435)
Household Size	-0.174***	0.840***	-0.206***	0.814***	-0.252***	0.778***	-0.299***	0.741***
	(0.00607)	(0.00510)	(0.00537)	(0.00437)	(0.00584)	(0.00454)	(0.00771)	(0.00572)
Head age	0.0190***	1.019***	0.0198**	1.020***	0.0215***	1.022***	0.0223**	1.023***
	(0.00151)	(0.00154)	(0.00122)	(0.00124)	(0.00119)	(0.00121)	(0.00139)	(0.00142)
Depend Ratio	-0.593***	0.553***	-0.561***	0.571***	-0.559***	0.572***	-0.554***	0.575***
	(0.0224)	(0.0124)	(0.0194)	(0.0111)	(0.0202)	(0.0116)	(0.0251)	(0.0144)
Head Gender	-0.455***	0.635***	-0.305***	0.737***	-0.274***	0.760***	-0.233***	0.792***
	(0.0760)	(0.0483)	(0.0592)	(0.0437)	(0.0562)	(0.0428)	(0.0636)	(0.0504)
Head Married	-0.643***	0.526***	-0.774***	0.461***	-0.696***	0.499***	-0.715***	0.489***
	(0.154)	(0.0808)	(0.115)	(0.0530)	(0.0977)	(0.0487)	(0.0994)	(0.0487)
Flush Toilet	0.339***	1.404***	0.349***	1.418***	0.416***	1.516***	0.542***	1.720***
	(0.0461)	(0.0648)	(0.0389)	(0.0551)	(0.0402)	(0.0609)	(0.0515)	(0.0886)
Rural	0.0973**	1.102**	0.0470	1.048	0.00558	1.006	-0.0213	0.979
	(0.0418)	(0.0461)	(0.0348)	(0.0365)	(0.0348)	(0.0350)	(0.0419)	(0.0411)
Sindh	0.368***	1.445***	0.320***	1.378***	0.310***	1.363***	0.347***	1.415***
	(0.0631)	(0.0912)	(0.0522)	(0.0720)	(0.0529)	(0.0721)	(0.0654)	(0.0925)
KPK	0.910***	2.485***	0.744***	2.105***	0.618***	1.855***	0.599***	1.820***
	(0.107)	(0.267)	(0.0826)	(0.174)	(0.0783)	(0.145)	(0.0903)	(0.164)
Balochistan	0.346***	1.414***	0.426***	1.530***	0.399***	1.490***	0.245**	1.277**

	(0.0939)	(0.133)	(0.0786)	(0.120)	(0.0813)	(0.121)	(0.107)	(0.136)
Constant	5.437***	229.7***	3.946***	51.72***	2.291***	9.889***	0.0542	1.056
	(0.449)	(103.2)	(0.357)	(18.48)	(0.354)	(3.498)	(0.437)	(0.461)
In this table we have reported GOLM to demonstrate the impact of shock on different quantiles of calories intake. Coefficients of shock variables are declining as we move from lowest to higher quantile, which means shocks are hurting more to household in lower quantile.								

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

Table-3.11B: Generalized Ordered Logit Model on Shocks and Households' Income Quantiles								
	(1)	1	(2)	2	(3)	3	(4)	4
Reference	GoLogit	Odd Ratio	GoLogit	Odd Ratio	GoLogit	Odd Ratio	GoLogit	Odd Ratio
Fifth (Highest)	**Lowest Quantile**		**Second Quantile**		**Third Quantile**		**Fourth Quantile**	
Average Flood	-2.902***	0.129***	-2.493***	0.0754***	-1.950***	0.0669***	-2.315***	0.170***
	(0.443)	(0.0661)	(0.384)	(0.0323)	(0.401)	(0.0293)	(0.516)	(0.0920)
Flood Shock	-0.258***	0.713***	-0.157***	0.848**	-0.120*	0.896*	-0.159*	1.002
	(0.0700)	(0.0558)	(0.0589)	(0.0544)	(0.0616)	(0.0582)	(0.0841)	(0.0777)
Average Rainfall	0.0672	0.918*	0.0685**	1.061	0.110***	1.085**	0.0992**	1.138***
	(0.0439)	(0.0417)	(0.0343)	(0.0395)	(0.0336)	(0.0396)	(0.0407)	(0.0493)
Rainfall Shock	0.307***	0.826***	0.222***	0.840***	0.184***	0.865***	0.0947**	0.978
	(0.0444)	(0.0356)	(0.0341)	(0.0304)	(0.0325)	(0.0304)	(0.0378)	(0.0401)
Average Temperature	0.624***	0.647***	0.394***	0.627***	0.402***	0.695***	0.242***	0.749***
	(0.0808)	(0.0555)	(0.0665)	(0.0448)	(0.0670)	(0.0510)	(0.0830)	(0.0694)
Temperature Shock	0.673***	0.670***	0.417***	0.643***	0.412***	0.705***	0.235***	0.746***
	(0.0814)	(0.0582)	(0.0670)	(0.0464)	(0.0676)	(0.0521)	(0.0838)	(0.0696)
Head Agriculture	0.693***	5.293***	0.520***	2.838***	0.475***	1.968***	0.461***	1.522***
	(0.0707)	(0.354)	(0.0549)	(0.167)	(0.0527)	(0.116)	(0.0613)	(0.107)
Head Self-employed	0.177***	12.11***	0.0564	5.335***	0.0815	2.964***	0.0293	2.267***
	(0.0679)	(1.013)	(0.0548)	(0.340)	(0.0536)	(0.176)	(0.0632)	(0.149)
Head Paid employee	-0.191***	6.884***	-0.271***	3.082***	-0.218***	1.992***	-0.218***	1.487***
	(0.0590)	(0.415)	(0.0475)	(0.163)	(0.0463)	(0.104)	(0.0541)	(0.0892)
Household Size	-0.174***	1.543***	-0.206***	1.520***	-0.252***	1.443***	-0.299***	1.328***
	(0.00607)	(0.0148)	(0.00537)	(0.0117)	(0.00584)	(0.00976)	(0.00771)	(0.00876)
Head age	0.0190***	1.020***	0.0198***	1.024***	0.0215***	1.026***	0.0223**	1.027***
	(0.00151)	(0.00155)	(0.00122)	(0.00138)	(0.00119)	(0.00144)	(0.00139)	(0.00177)
Dependency Ratio	-0.593***	0.565***	-0.561***	0.504***	-0.559***	0.474***	-0.554***	0.484***
	(0.0224)	(0.0152)	(0.0194)	(0.0119)	(0.0202)	(0.0116)	(0.0251)	(0.0145)
Head Gender	-0.455***	5.247***	-0.305***	3.941***	-0.274***	3.326***	-0.233***	2.760***
	(0.0760)	(0.362)	(0.0592)	(0.270)	(0.0562)	(0.251)	(0.0636)	(0.266)
Head Married	-0.643***	1.234*	-0.774***	0.875	-0.696***	0.799**	-0.715***	0.766**
	(0.154)	(0.142)	(0.115)	(0.0912)	(0.0977)	(0.0867)	(0.0994)	(0.103)
Flush Toilet	0.339***	2.223***	0.349***	2.500***	0.416***	2.664***	0.542***	2.871***

	(0.0461)	(0.105)	(0.0389)	(0.107)	(0.0402)	(0.129)	(0.0515)	(0.203)
Rural	0.0973**	0.467***	0.0470	0.448***	0.00558	0.463***	-0.0213	0.480***
	(0.0418)	(0.0234)	(0.0348)	(0.0176)	(0.0348)	(0.0174)	(0.0419)	(0.0209)
Sindh	0.368***	0.954	0.320***	1.119**	0.310***	1.017	0.347***	0.813***
	(0.0631)	(0.0641)	(0.0522)	(0.0640)	(0.0529)	(0.0607)	(0.0654)	(0.0617)
KPK	0.910***	0.401***	0.744***	0.374***	0.618***	0.457***	0.599***	0.500***
	(0.107)	(0.0432)	(0.0826)	(0.0327)	(0.0783)	(0.0385)	(0.0903)	(0.0489)
Balochistan	0.346***	1.198	0.426***	1.115	0.399***	0.993	0.245**	0.724***
	(0.0939)	(0.135)	(0.0786)	(0.0995)	(0.0813)	(0.0881)	(0.107)	(0.0798)
Constant	5.437***	0.00108***	3.946***	0.0365***	2.291***	0.0179***	0.0542	0.865***
	(0.449)	(0.000526)	(0.357)	(0.000146)	(0.354)	(0.105)	(0.437)	(0.3905)
In this table we have reported GOLM to demonstrate the impact of shock on different quantiles of calorie income. Coefficients of shock variables are declining as we move from lowest to higher quantile, which means shocks are hurting more to household in lower quantile.								

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

Table-4.1A: Summary Statistics of the Variables

Variable		Mean	Std. Dev.	Min.	Max.	Observations
Prevalence of Undernourishment	Overall	13.79603	9.320001	2.5	63.2	N = 987
	between		8.513599	3.35	47.47375	n = 94
	Within		4.3847	-19.8877	37.75978	T-bar = 10.5
Household Expenditure Growth	Overall	2.600629	5.633137	-35.5399	65.1811	N = 987
	between		2.551537	-9.6106	13.78697	n = 94
	Within		5.099377	-23.8822	59.11583	T-bar = 10.5
Household Asset Index (hai)	Overall	69.96261	24.52373	3.92	99.14	N = 987
	between		24.08667	6.545	97.32875	n = 94
	Within		6.714735	44.71386	91.92261	T-bar = 10.5
Social Protection Share to GDP %	Overall	5.720466	4.003595	0.3	18.5	N = 987
	between		3.746672	0.8125	16.575	n = 94
	Within		1.516955	-4.66453	14.88297	T-bar = 10.5
Economic and Environmental Vulnerability Index (EVI)	Overall	19.8741	16.9875	2.36	100	N = 987
	between		16.33099	2.78125	93.155	n = 94
	Within		7.393395	-28.2647	58.2591	T-bar = 10.5
Dry Index	Overall	32.18132	39.66087	0	100	N = 987
	between		39.13435	0	100	n = 94
	Within		1.667865	17.10007	49.83231	T-bar = 10.5
Victim Index	Overall	59.60747	29.38422	0	100	N = 987
	between		27.34496	0	98.1425	n = 94
	Within		10.24872	-20.0825	130.4943	T-bar = 10.5
Dependency Ratio	Overall	66.34693	20.84955	15.7431	111.939	N = 987

	between		19.78156	22.98863	109.5005	n = 94
	Within		5.821625	44.16105	110.4125	T-bar = 10.5
Current Account	Overall	-2.0262	20.48857	-65.0289	311.761	N = 987
	between		18.5548	-29.2484	156.0601	n = 94
	Within		11.7192	-160.113	153.6747	T-bar = 10.5
FDI Index	Overall	4.671461	7.243667	-4.61459	103.337	N = 987
	between		4.762176	0.018877	25.16949	n = 94
	Within		5.505181	-20.196	82.83897	T-bar = 10.5
GDP Growth per-capita	Overall	2.629501	4.730138	-22.3123	56.7882	N = 987
	between		2.240774	-4.11432	10.3913	n = 94
	Within		4.248302	-22.1859	53.39913	T-bar = 10.5
Inflation	Overall	6.700032	15.67276	-18.1086	411.76	N = 987
	between		7.078518	0.771859	55.5741	n = 94
	Within		14.20394	-47.4843	362.8859	T-bar = 10.5
This table shows the descriptive statistics of macro-level well-being, environmental and economic shocks and control variables mean, minimum and maximum values.						