The Sensitivity of Poverty Analysis to Dimensionality and Distribution Sensitivity:

Evidence from District Level of Pakistan

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ABSTRACT

An awareness of how the findings from poverty analyses may change following introduction of multidimensional poverty measures is crucial for policy makers. This thesis highlights the changes in results of poverty analysis in Pakistan, which is a setting where multidimensional poverty measures recently either supplanted or supplemented money-metric poverty measures. The analysis relies on district-level poverty estimates, every second year from 2004 to 2014, calculated from the Pakistan Social and Living Standards Measurement survey and Household Income and Expenditure survey. Around two-thirds of districts show an opposite movement in poverty trends when comparing money-metric and multidimensional poverty trends. The convergence in poverty rates across districts is evident for money-metric poverty measures but not for multidimensional poverty measures. Relatedly, spillover effects on nearby districts matter for convergence in money-metric poverty but not for multidimensional poverty. The districts with high initial money-metric poverty estimates are catching-up to other districts but the districts with high initial multidimensional poverty are not. For reducing money-metric rural poverty (in particular the Squared Poverty Gap index) the growth of secondary towns is significant; however, for reducing multidimensional rural poverty it is not. The unconditional cash transfer programme, Benazir Income Support Programme (BISP), helps to reduce district-level money-metric poverty more than multidimensional poverty. Community-based targeting used in identification of poor households under BISP is more effective than Proxy Means Testing for money-metric poverty but the opposite is true for multidimensional poverty. Hence, given these varied patterns for money-metric and multidimensional poverty, policy makers need to be cautious when they draw conclusions from poverty analysis, particularly in settings where the multidimensional measures are either supplementing or supplanting money-metric poverty measures relied on previously.

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In the name of Allah who is the most beneficial and the most merciful.

My journey of PhD has been a roller coaster. It has its own interesting ups and downs that made it one of its own kind. But what hooked me to PhD was my cause and my supervisors. I was blessed to have Professor John Gibson as my mentor. I am grateful to Allah for manoeuvring my life and bringing me to this experience full of knowledge and learning.

I remember the first day I met Professor, (I know no one addresses him as professor but I do, he is an inspiration to me). Anyway, the first thing he taught me was the very simplest of things, in NZ they do not say ‘z’ as zee but its pronounced as ‘zaid’. And after that I never said zee. That was the smallest of the first few things in first few minutes I learnt, and I knew in that instance my PhD journey is going to be full of knowledge and learnings because of him. My learning curve was steep which I am happy about. Just by observing how he works, his work ethics, his work-life balance, all of these things teaches a lot. He is the model of excellence to me. I may not be his best of the best students, but he has been the best supervisor. He has taught me how to identify an issue, how to analyse and, most importantly, how to convey the results and build narrative. I want to thank Geua-Boe Gibson as well. She is amazing. I have so many reasons to thank her, but I won’t be able to mention them all here. My second supervisor, Susan, she is the most humble person I have met. She take care for her students; she makes sure all her students comprehends what she is teaching. She was always there for me. Thank you, Susan Olivia. I hope the connections I have built with my supervisors stay forever. I would like to thank Maria Neil for being her optimistic self. If you are stuck and you need to know what to do next, she is the person, you go to her room and discuss and when you come out of that door you have the solution. I also want to convey my gratitude to Sayyeda Bano, Steven Tucker, Gazi Hassan and Frank Scrimgeour.

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Preface

I remember driving to the city centre one day, there was an 8-years-old boy knocking at my window begging for money. I rolled down the window and asked, "Why are you begging, my child? If you want to make something out of your life you need to study, you need to go to school." I even told him that primary education in government schools is free. I wanted him to understand that begging will not take him anywhere in future, and he needs to go to school. And obviously, I was doing it because we have this notion that poor people chose to go for the easiest way to earn money and sometimes it is their parents who make them do it. But no. I was wrong! which I realized after the conversation I had with him. He was out begging on the road because his father died. I felt the pain, I even felt my body temperature dropping.

His father was a labourer. It is unreasonable to expect a labourer's family to have savings. Even the government is of no support in those situations because government does not have flexible financial support programmes which can provide support instantly. Labourer in my country earn wages based on the hours they work in a day and if they do not find work, they do not get paid for that day. Also, they get just the minimum wage. That day I decided I must do something for the vulnerable segment of our society. Doing PhD on the topic of poverty and trying to understand its dynamics is just the starting point, I have a long way to go. But we will get there one day when there will be no poverty. Amen.

You cannot invest in future if your present is not secure.

Zaira Najam

TABLE OF CONTENTS

CHAPTER 1

Introduction

Uncertain situations like COVID-19 highlight the need for efficient policy interventions to alleviate poverty. The least which can be done to prepare societies before such unforeseen situations is to understand the poverty profile and poverty trends, and also the weaknesses of the evidence base. The pandemic has disrupted the goal of eradicating poverty in all forms and dimensions by 2030 (the first Sustainable Development Goal (SDG) of the United Nations (2015)). The World Bank's "nowcast" (preliminary estimates) of post-pandemic poverty are that there are 119 – 124 million people pushed into poverty, making a total of 703 – 729 million people living in extreme poverty worldwide (Mahler et al., 2021).

It is crucial that policy makers better understand poverty trends and sensitivity of these to different poverty measures. Likewise, they should understand how results on the efficiency of targeting the poor, and the impacts of social safety net programmes differ across poverty measures. These issues are especially important in Pakistan, with limited resources, low GDP growth rates (averaging around 4% per annum in the last two decades), high population growth rates (averaging 2.2% per annum in the last two decades) and with one quarter of the population living below the national poverty line (US $1.1 per day), and struggling to achieve the SDGs (World Bank, 2020).

Pakistan is becoming crucial in supporting regional trade after China-Pakistan Economic Corridor (CEPC), a project part of One Belt One Road initiative. CPEC will have positive impact on Iran, Afghanistan, Central Asian Republic, and the region. The benefits can only be widespread if the social and security conditions are viable. It has been widely accepted that in the presence of impoverished and deprived fraction of the population there is exploitation of labour, crimes and terrorism. High incidence of poverty hinders regional growth and stability.

Therefore, the geographical and political significance of Pakistan makes understanding sensitivities of Pakistan's poverty trends crucial. The pandemic has further worsened the conditions of the vulnerable segment of the population in Pakistan.

Notwithstanding limited resources, Pakistan has committed to eradicating poverty. There have been a few poverty alleviation programmes in place for the last 30 years, implemented through Pakistan Bait-ul-Mal, Benazir Income Support Programme, Zakat, Employees Old Age Benefit Institute, Workers Welfare Fund and Pakistan Poverty Alleviation Fund. The proportion of the population living below the national poverty line has fallen rapidly in the past two decades, going from two-thirds of the population in 2000 to just one-quarter in 2015 (World Bank, 2020). Despite this progress, there were still almost 50 million people living below the national poverty threshold in 2015. Moreover, the progress seen at the national level has not been uniformly repeated across all parts of the country.

The economic conditions for the poor and vulnerable in Pakistan has worsened during the pandemic. GDP has fallen at least 0.5 percent, while growth was already on a declining trend since 2018, when a Balance of Payment crisis hit Pakistan, and the growth rate fell to 2.1 percent from 5.5 percent the year before (Government of Pakistan, 2020). The lingering balance of payment crisis coupled with the pandemic has lowered development expenditure, to just 1.4 percent of GDP in 2020 from 3.1 percent in 2018. To support the poor segment of society, Government of Pakistan (GoP) increased its allocation under an Ehsaas Programme from Rs 187 billion (US $ 1.17 billion) to Rs 208 billion ($1.30 billion) in FY 2021 (Government of Pakistan, 2021). However, this 11 percent rise is not in proportion to the vulnerable population falling into poverty. In 2015-16, 24.3 percent of the population were living below the poverty line, while 19.9 percent were identified as vulnerable to poverty if they face an economic shock (Planning Commission Pakistan, 2018). This makes 44 percent of the population vulnerable during the pandemic. Therefore, in such crisis, where budgeted relief packages cannot cover required needs, it is important to have information on the most vulnerable households and where they are clustered so that they can be well targeted. However, identification and targeting is a complex question when there are different poverty indicators available for poverty measurement.

Peter Drucker said "If you can't measure it, you can’t manage it."[1] Taking these words in the context of poverty measurement can help one understand the struggle since the last century for a better poverty measure. In particular, struggle towards a poverty measure that is more comprehensive and explanatory so that policies can be devised to uproot poverty in the most efficient and effective way, leading to successful achievement of the SDGs. In the area of poverty measurement, there has been an evolution from conventional, money-metric poverty measures to non-conventional, multidimensional poverty measures with increased emphasis on compliance to poverty axioms like distribution sensitivity.

Recently there has been increased use of multidimensional poverty measures, following earlier discussion of these in the literature. Since the start of this century, the *Human Development Report* started to see poverty as a multidimensional phenomenon. Over the last decade, Oxford Poverty and Human Development Initiative (OPHI) at the University of Oxford and the Human Development Report Office of the United Nations Development Programme introduced the Multidimensional Poverty Index—MPI (Alkire et al., 2011; Alkire & Santos, 2014; UNDP, 2010). They have carried forward the philosophy of Sen (1980, 1992, 1997, 1999, 2009) in the development of this indicator. The philosophy of Sen is to conceptualise poverty in the form

[1] These words are quoted in a World Bank Blog by Patrinos (2014)

of a set of functions and capabilities which a person should possess. The MPI is widely used, with more than 100 countries reporting it on an annual basis.

Yet the World Bank still uses conventional (money-metric) poverty measures in more than 145 countries for analytical and operational work on poverty. While the World Bank acknowledges multidimensionality of poverty, the former director of the World Bank Research Department notes concerns around an assumption required to calculate the MPI (Ravallion, 2011):

> it is one thing to agree that consumption of market commodities is an incomplete metric of welfare - and that for the purpose of assessing poverty one needs to also account for indicators of non-market goods and services - and quite another to say that a single 'poverty' measure should embrace all these things. (p. 246)

These two types of poverty measures — conventional money-metric and non-conventional multidimensional — have attracted attention from different researchers. But when it comes to policy advice, evidence-based insights are required. There is no study that I am aware of, neither on Pakistan nor on any other country, that compares poverty trends using these two types of poverty measures to identify if they reveal the same direction of progress towards poverty eradication. The studies which have analysed poverty in Pakistan using either money-metric or multidimensional poverty indices are listed in Appendix I. This existing literature does not answer whether using two types of measures, which satisfy different axioms, show different poverty trends or not. Therefore, this is the first question addressed in this thesis, focused at the district-level of Pakistan (Chapter 4). This thesis will work as a stepping stone in providing more evidence on how poverty in Pakistan will be analysed and understood and how poverty alleviation strategies will be planned and assessed.

In Pakistan, a spatially disaggregated analysis is critical for policy advice. Historically, the National Finance Commission (NFC) made fiscal transfers to the provinces from the Federal Divisible Pool on the basis of each province's share of the national population. However, since 2009 the NFC award criterion changed to use multiple conditions. Now the share is calculated using four factors for the provinces: Population 82 percent, Poverty backwardness 10.3 percent, Revenue collection or generation 5.0 percent, and Inverse population density 2.7 percent. Based on this, the NFC pool currently allocates nine percent to Balochistan, 15.47 percent to Khyber Pakhtunkhwa, 51.22 percent to Punjab, and 24.31 percent to Sindh (Aziz, 2010). Moreover, under the 18th Constitutional Amendment, provinces have more responsibilities for managing and planning their resources. They have the power in managing and implementing development projects in their districts. In the wake of this increased provincial responsibilities, the provincial governments need more region specific comparisons and outlooks to plan their projects for improving the welfare of people. Pakistan is fairly advanced in decentralization, which is an approach followed in several populous countries (e.g. Indonesia) and which often creates a need for surveys (e.g. HIES which is representative at the provincial level) to have results available for analysis at each of the sub-levels of the administrative hierarchy (like district level in Pakistan). Therefore, in this research, the poverty analysis is conducted on the district-level of Pakistan so that provinces can be informed about the poverty profile of their districts.

Using information on where the poor population are clustered to target regional development programmes to those areas may be an effective way to alleviate poverty. This targeting might be effective even if there is insufficient capacity to target poor individuals or households. Effective targeting is relevant for Pakistan given the disparity amongst the provinces. Punjab accounts for 54.3 percent of Pakistan's GDP, Sindh 29.2 percent, Khyber Pakhtunkhwa 12.0

percent, and Balochistan just 4.5 percent (Pasha, 2019 and GDP per capita). The same disparity is observed in terms of GDP per capita, Punjab per capita GDP Rs 54,672, Sindh per capita GDP Rs 69,417, Khyber Pakhtunkhwa per capita GDP Rs 53,523 and Balochistan per capita GDP Rs 31,370 (Pasha, 2015). Sindh has the highest Human Development Index (HDI) value (0.574) of all provinces, with Punjab almost as high (0.572). Khyber Pakhtunkhwa is third (HDI 0.546), and Balochistan is much lower with an HDI value of 0.473 (Pasha, 2019).

Although understanding spatial patterns of poverty is important for better targeting and resource management, regional development policy should also be based on the evidence of changes in poverty over time. If the regions with high poverty rates in the past experience slower rates of poverty reduction than other regions this implies the benefits of economic development are not spreading to all regions uniformly (Gibson et al., 2005). Hence, it is important to know for districts (sub-provincial level) that started off at the impoverished end of the welfare spectrum, if they are catching up with other districts over time. This is the second question I have addressed in my thesis (Chapter 5).

If I further investigate the district-level, the major impoverished segment of the districts lies in the rural areas. In all provinces of Pakistan, rural areas have lower per capita GDP than urban areas (Pasha, 2019). However, the magnitude of differences between rural and urban areas varies across provinces. Sindh has the highest gap between urban and rural HDI, followed by Balochistan, then Punjab and Khyber Pakhtunkhwa (UNDP, 2021). In the era of increased urbanisation, knowing what type of urban area—big cities or secondary towns—is impactful in raising welfare of rural areas is important. This is because it is cheaper to create jobs in secondary towns than in big cities (Kanbur et al., 2019) and it is more viable for rural migrants to perch into and find employment in secondary towns (Ingelaere et al., 2018).

Given the varied differences between urban and rural regions across provinces in Pakistan, it is important to investigate and capitalise on any connection of poverty reduction in rural areas with city growth and secondary town growth. The impact of city growth and secondary town growth on poverty reduction in rural areas is also studied in this research. This is the third question researched in this thesis (Chapter 6).

As mentioned earlier Pakistan has average GDP growth of 4 percent per annum in the last two decades, however, the growth in any country does not solely ensure uniform distribution of opportunities and benefits to all segments of the society (Ravallion, 2001). More so, countries with high inequality find it harder for the benefits to reach the deprived segment of the society (Fosu, 2011). To address this unequal distribution of benefits of growth, countries devise social safety net programmes to reach out to the underprivileged areas. In the case of Pakistan, the effectiveness of social safety net programmes needs to be examined. During last the 30 years there have been a few support programmes some of which were replaced by the Benazir Income Support Programme – BISP (Government of Pakistan, 2009). BISP is so far the largest social safety net programme in Pakistan. It was initiated in 2008 when the economy was going through the fallout due to global financial crisis and the highest inflation in last 30 years (20% in 2008 from 7.7% in 2007). The objective of BISP is to financially support poor households. In order to reach the poorest of poor households, BISP has been through two targeting phases, first community based and then Proxy Mean Testing based.

The success of a social safety programme relies on close targeting of deprived households and success can be accessed by the reduction in poverty rates. There has been substantial reduction in people living under the nationally defined poverty line, decreasing from two-thirds in 2000 to just one-quarter in 2015 (World Bank, 2020). But, because of the existing disparity among regions, it is important to investigate whether this rapid reduction in poverty is across all districts, and if the BISP payments made to the poor households in all districts are effective in reducing both money-metric and multidimensional poverty. This is the fourth question I have researched in this thesis (Chapter 7).

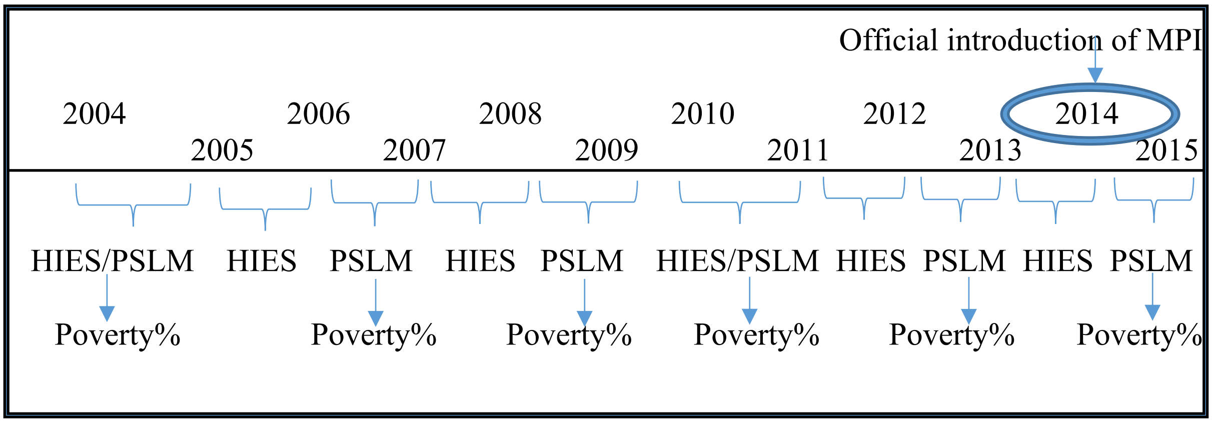
In a nutshell, the significance and contribution of this thesis is that it observes, whether the poverty clusters, trends in poverty numbers over time, and effectiveness of poverty eradication initiatives, are impacted by the introduction of dimensionality and the axiom of distribution-sensitivity in poverty measurement techniques. To give insights on these questions I have unwrapped the answers layer by layer.

First, to present an overarching picture, I compared differences in temporal poverty trends at the district-level when estimated with conventional money-metric poverty measures versus with non-conventional multidimensional poverty measures (the first research question). For both types of measures I consider distributionally sensitive and insensitive indices. Then, I have analysed the poverty status of districts (the second research question), whether districts with high poverty rates in earlier years are catching-up at a faster rate of poverty reduction than their counterparts, and more importantly, if this catching up phenomenon is sensitive to the choice of poverty measure. Third, because of the varied urban-rural gap across provinces I have researched whether two types of urban areas — big cities and secondary towns — are equally influential in reducing rural poverty and if the relationship between urban growth and rural poverty differs if dimensionality and the axiom of distribution-sensitivity are considered in poverty measurement techniques. To conclude the district-level poverty analysis, the government intervention in reducing poverty is also analysed in the fourth research question. I have examined the effectiveness of BISP in reducing district-level poverty, whether conclusions about effectiveness of BISP change when the multidimensional and distribution-sensitive poverty measures are used in the analysis.

To answer these research questions I have used the Pakistan Social and Living Standards Measurement Surveys (PSLM) and the Household Income and Expenditure Surveys (HIES) administered from 2004 to 2014. Both PSLM and HIES data are used to calculate conventional and non-conventional poverty measures. In the class of conventional poverty measures Headcount Index, Poverty Gap Index (distribution insensitive), and Squared Poverty Gap Index (distribution sensitive) are calculated. In the class of non-conventional poverty measures, the Multidimensional Poverty Index (which is distribution insensitive (Alkire & Foster, 2011)), and the Multidimensional Distribution-sensitive Poverty Index (Datt, 2019) are calculated. Using PSLM combined with HIES has made it possible to generate biennial poverty estimates (six times) from 2004 to 2014 at National, Provincial and District-levels of Pakistan. The Small Area Estimation is used to calculate conventional poverty measures at the district-level (the detailed discussion is in the fourth chapter).

Government of Pakistan has been reporting money-metric based headcounts of poverty but then in 2014 it made a transition towards calculating multidimensional poverty measures (See Figure 1.1). Government of Pakistan used HIES for estimating national and provincial poverty headcounts (money-metric). For estimating multidimensional poverty estimates at national, provincial and district level it used PSLM. There are no official or unofficial money-metric poverty estimates available at the district level. So in this study I did a form of 'back-casting' to apply the multidimensional poverty index (MPI) that Pakistan settled upon (for the post-2014 period) to survey data that are from earlier periods, in order to create an overlap where both money metric and multidimensional poverty estimates are available for the same time periods, and at the same level of administrative geography.

Figure 1.1: Timeline of survey periods and the years poverty measures estimated for



This process is needed to provide a ‘testing ground’ or a ‘counterfactual’ to understand differences in behaviour of the two types of poverty measures in the Pakistan context. Absent this exercise, analysts will not know whether changes in the poverty record for Pakistan reflect the changes in measurement approach, or instead are due to real on-the-ground changes in the actual situation. This use of back-casting means that it is appropriate to use the administrative geography as it was in 2004.[2] Also, the multidimensional index that I have estimated follows the construction of the official MPI for Pakistan, so analyses with different weights and allowing for different correlation patterns is not needed here, although it typically would be crucial for a study that constructed a new MPI.

My results for the first research question show that poverty trends for money-metric and multidimensional poverty measures are not identical. Around two-thirds of districts show opposite trends for at least two of the five spells between surveys. Secondly, districts with an initially high poverty rate are catching up to their counterparts, if poverty is measured using

[2] The district borders prevalent in 2004 are used in the study and the provincial treatment adopted by PBS is used in allocating districts. Therefore, Islamabad is treated as if it is a district in Punjab Province. The study districts do not include areas in former FATA, GB, and AJK due to inconsistency in availability of data.

conventional money-metric measures but not if multidimensional poverty indices are used. Also, cross-district spillovers from spatial regression models matter only for money-metric poverty and not multidimensional poverty.

When further disaggregating, to consider rural poverty within districts, growth in big cities is not poverty reducing when poverty is measured using multidimensional poverty measures. It is the big cities that have grown faster than secondary towns in Pakistan, based on an analysis of night-time lights. Yet for the headcount index of money-metric poverty, growth in big cities helps to reduce rural poverty, although that growth does not seem to reach the poorest of the poor (based on findings for the squared poverty gap index). However, growth of towns on their extensive margin (that is, expansion of lit area rather than increased brightness) is associated with reduced money-metric and multidimensional rural poverty measures. To have better results from urban growth and development, the Government of Pakistan may need to put more priority towards growth of secondary towns.

I found that the Government of Pakistan's biggest poverty eradicating initiative, BISP, has been significant in reducing poverty; however, it is more impactful in reducing money-metric poverty than multidimensional poverty. Also, the Community Based Targeting has been more effective in reducing money-metric poverty whereas, Proxy Mean Testing based targeting is effective in reducing multidimensional poverty.

Overall, this thesis contributes to the literature on poverty analysis by showing the multiple ways by which using multidimensional poverty measures may reveal different patterns to what has been previously seen with money-metric poverty measures. These differences signify the importance of a comparative outlook for the identification of vulnerable segments of the society and in judging the success of policy interventions using two types of poverty measures. After the introduction of multidimensional poverty measures, poverty patterns are no longer seen in the usual manner that was established from prior studies using money-metric poverty. At least in the transition period while multidimensional poverty measures supplant or supplement money-metric measures, policy makers need to be more cautious in the conclusions they draw from poverty analyses.

The remainder of the thesis is structured as follows. The second chapter describes the history of poverty measures, the evolution of welfare proxies from money-metric poverty measures to multidimensional poverty measures, and gives a poverty snapshot of the world highlighting how comparative thinking is essential to draw conclusions on progress in poverty eradication. The third chapter presents an economic snapshot of Pakistan, highlighting the need for this comparative study in the context of Pakistan. The fourth chapter answers the first research question on differences in poverty trends when dimensionality and distribution sensitivity are considered in poverty measurement. The fifth chapter answers the second research question on whether districts with high initial poverty rates are converging to their counterparts considering dimensionality and distribution sensitivity in poverty measures. The sixth chapter answers the third question on whether big cities or secondary towns are more influential in reducing rural poverty, calculated using money-metric and multidimensional poverty measures. The seventh chapter answers the fourth research question, of how effective is the BISP program in reducing money-metric and multidimensional poverty. The last chapter provides a comprehensive conclusion to the thesis.

CHAPTER 2

The Subject of Poverty

The state of welfare attenuation, poverty, has gone through a long journey to be finally recognized as a social issue that needs policy attention. In literature, the welfare measurement varies from money-metric-utility to non-utility approaches. The first part of this chapter presents a snapshot of the journey poverty has taken to be recognised as a social issue and the welfare measurement techniques in literature. The second part gives a brief overview of the poverty estimation techniques and poverty indices. The third part presents poverty snapshot of the world, and how the comparative thinking is essential while drawing conclusions regarding the progress in poverty eradication

2.1 History of Poverty

A revisit of poverty historic records is salient in understanding the need for a single, yet comprehensive, estimate of poverty. The pages of history reveal how the word poverty emerged and thereafter how and why the need for antipoverty policies was realised. Poverty was not used to be considered a matter to deal with, instead, centuries ago, it was considered as a pre-condition for growth – a social good. Proponents of mercantilism treated poverty as an essential for economic growth and power. It took a long time for the social scientists to identify it as the state's responsibility to address this aggravating and bourgeoning social bad.

A psychologist, Vives (1526), in the early sixteenth century referred to poverty as a social bad and that it has repercussions on the privileged class of the society. He referred to poor people as a threat to the security and health of the privileged, calling the need for antipoverty policies. The concern at that time was not the welfare of unprivileged class but the disturbance created in the lives of the privileged because of the presence of poor in the society.

A further step back into the history presents Confucius 500 BC (presented in detail by Li, 2012), he had the idea of the six calamities which government should address: early death, sickness, misery, repulsive appearance, weakness, and poverty. Although Confucius mentioned poverty in his calamities, his focus was not the poverty associated with wealth inequality but with the social order. In his view, social order should be maintained in the society as in the presence of social order there will be no poverty. Dawson (1915) quoted Confucius' "When the people keep their respective places, there will be no poverty; when harmony prevails, there will be no scarcity of people; when there is repose, there will be no rebellions" (p.186).

During the BC era the focus was usually on maintaining the social order, the natural order in the society. The demarcation of capitalist (rulers / owners) and the working (labour) class was stressed to be maintained and ensured for the repose in the society. There was little or no discussion found in literature about the redistribution of wealth in the favour of unprivileged during that time. Even in the debate on charity in literature, during 50 BC, Marcus Mullius Cicero a roman thinker distinguished between charity and justice (Wood, 1991). He mentioned that charity was a matter of choice but justice was a matter of government's responsibility to ensure. He did not support wealth redistribution per se.

Not only do the philosophers and sociologists of that time favour the natural order which has nothing to do with eradicating poverty but neither the economists of that time considered antipoverty policies. Instead, back then, the dominant school of thought, mercantilist, saw poverty as an essential driver for development as the focus was on increasing exports. De Mandeville (1732) argued that economic growth occurred through increased trade with the help of poor providing cheap labour (low wages).

During the late eighteenth century, the enlightenment about poverty gained momentum when Smith in *Wealth of Nations* (1776) lambasted mercantilists and talked about the welfare of people in terms of command over commodities. He mentioned that development actually is progress against poverty. The first empirical analysis of poverty ‘the state of poor’ was done by Eden (1797), thereafter the debate over redistribution and the role of government was highlighted in literature. Rousseau (1754) carried forward Hobbes' (1651) theory of the social contract; how the performance of government is to be gauged against its opposite, the natural state (the absence of government). He emphasized the role of the state for repose in society. Kant (1785) also discussed the role of the government in benevolence as he argued that benevolence on private grounds will generate unequal relations between giver and the taker, so the state should take that responsibility. Around the same time Bentham (1789) presented the idea of utilitarianism. He argued that social choices should be made considering the utility of individuals by subverting the rights-based theory of social contract. He argued that the diminishing marginal utility should be considered by the government to perform redistributive role.

Before the nineteenth century, in the literature, the debate was on finding justification for anti-poverty laws and policies but later the debate revolves around the benefits and curses of the anti-poverty policies. The economists of that time, Malthus (1806) and Ricardo (1817), were not in the favour of antipoverty policies. Malthus argued that by giving a cushioning wage, there would be growth in the population which would lead to increased labour supply and hence will push back the wage rate and end in misery. Ricardo argued that anti-poverty policies decrease labour productivity. In his view, such policies would augment wages and translate into increased population and labour supply. With the increase in labour supply, marginal labour productivity would decrease. Townsend (1786) and Turnor (1818) are also among the list of economists who decried anti-poverty policies for their overriding negative implications for the economy. During the debate over anti-poverty policies, Marx (1887), emerged as a socialist, and argued that the roots of poverty are in capitalism and so the solution is in socialism. This provoked another debate over the structure of economy for the welfare of the individuals.

The debate on different sorts and aspects of poverty and the estimation techniques bourgeoned during the start of twentieth century. Marshal (1920) argued that chronic poverty cause the absence of children's education in poor families which pulled them back into the poverty and created the vicious circle of poverty. Also, welfare estimation techniques for calculation of poverty is debated in literature. Bentham presented the classical utilitarianism argument for welfare estimation. Another follower of utilitarianism, Mill (1848) discussed the role of government in redistribution with a focus on maximizing the total utility of the society. Pareto (1905) argued for ordinal concept of utility for welfare estimation against cardinal utility approach and suggested pareto optimal condition could be achieved for maximum welfare of society in which no one can be better off without making anyone else worse off.

In the context of estimation techniques, poverty was estimated as the deprivation in the consumption or income of an individual and then evolved into estimating deprivation in multiple dimensions, a multidimensional approach. In the literature, economic welfare, a type of consequentalism, was targeted through various policies either implicitly or explicitly. Anti-poverty policies are generally set out to improve the welfare of deprived class of the society. These policies require an estimate of the deprivation faced by the people. The question then arises, deprivation in what aspect should be termed as poor. Usually deprivation in the context of welfare is considered poverty. In literature, the methods used to gauge welfare varies from money-metric utility function to multidimensional approaches. In the money-metric utility approach, the money value of the list of commodities which an individual choses for maximizing his utility level is calculated. In this way, on the basis of an individual's utility function, the utility function for the society is modelled. This is termed an individualistic approach. In utility-based welfare estimation, the preferences and the choices of individuals are taken into account in contrast to paternalism. In paternalism, the policy makers sets out their own judgement in modelling utility functions for the society. But, only market-based commodities were considered in that approach. Although non-market goods are also sought after for maximizing one's utility, which were ignored.

To simplify the inclusion of individual preferences in assessing utility and ultimately welfare, Rawls (1971) introduced a specific-deprivation approach. In that, only the preferences of disadvantaged people were considered. He argued that first an index should be developed to identify poor on the basis of primary goods and then their preferences should be considered. Opposed to both utility-based and specific-deprivation approaches, Sen (1980) introduced a capabilities approach. In his view for an individual to convert the commodities into well-being he requires a few capabilities. The lack of those capabilities should be considered for poverty analysing poverty.

Another dimension to welfare estimation was inclusion of social needs - people care about their acceptability in the society. Bourguignon and Atkinson (2000) presented a very simple approach to classify all those as poor who cannot attain both the absolute basic needs for survival and the minimum basic for social inclusion. In this debate for social inclusion, the concept of absolute and relative poverty was raised. In absolute poverty, the focus is on possession of basic commodities but in relative poverty, the relative standing of one individual with respect to the rest of the society is considered. Sen (1980) argued that poverty should be considered absolute in the space of capabilities and relative in the space of commodities.

The subject poverty has advanced from ‘being a means to an end’ to ‘an end in itself’. It started from being an evil for the privileged class which should be eliminated; to being welfare attenuating for the impoverished class and hence should be eliminated. The debate emerged from protecting the interests of rich people to protecting and supporting the impoverished class. Guarding and promoting the well-being of an impoverished class through anti-poverty policies requires poverty estimation, which can be based on welfare estimation or on a capability approach. For reference and comparison purposes, a single value of poverty is desired in the literature.

2.2 Poverty Estimation Techniques

In literature poverty indices are based on different theories and frameworks. There are some calculated using a single variable and some calculated using a multitude of variables. There are four questions to be answered for poverty estimation; **first,** in what context should deprivation be observed (what constitutes poverty)? **second,** what variable(s) is (are) to be considered for poverty estimation? **third,** how should the poverty cut-off be set; **fourth,** what poverty index should be used for poverty estimation?

First question: In what context should deprivation be observed (what constitutes poverty)? An advancement in literature is observed from considering deprivation in the context of welfare to deprivation in capabilities and functionings. After poverty was considered as a social bad for the society and anti-poverty policies were under way, the economic welfare of individuals was considered for poverty estimation.

In contrast to Hobbes and Rousseau’s social contract theory, Bentham (1789) presented the idea of utility, in which for the economic welfare, the focus should be on total utility of the society.

The individualistic approach is based on a utilitarian approach. In an individualistic approach, the social state of the society is evaluated by observing an individual's utility level – whatever maximizes the utility of an individual should be the focus in estimating welfare. The individualistic approach was an opposite to paternalism.

There were a few criticisms of the utility-based welfare estimation approach. First, it was identified that measuring utility was a difficult task. So, Pareto (1905) created the ordinal concept of utility for welfare estimation to replace the cardinal utility approach. He mentioned a pareto optimal condition should be achieved for maximising the welfare of society in which no one can be better off without making anyone else worse off. Second, everything should be included which increases the individual's utility level; that prompted the debate on irrational expectations (Ravillion, 1986). Third, the heterogeneity exists in individual's utility levels as there is welfare related to non-market goods (Pollak & Wales, 1979; Browning, 1992). Given the heterogeneity in the preferences of the individuals, Rawls (1971) suggested that at first, poor should be identified on the basis of primary commodities, then their preferences should be considered.

As an alternative to the utility based approach, Sen (1980) presented his idea of capability approach. He mentioned that the state of deprivation or absence of functionings should be the focus. He stated that functionings is the group of capabilities. Capabilities are the set of beings and doings - ability to live, healthy old age, being employed, being safe, able to participate in social and economic activities.

For the first question, two approaches are broadly classified: utility-based welfare approach; and the capability approach.

Second question: What variable(s) is (are) to be considered for poverty estimation? Different variables can be found in literature for estimating poverty under welfare and capability approaches.

Under the welfare approach, there is debate in literature either against or in favour of using consumption or income as a welfare measurement tool. Hicks (1939) presented the idea of money-metric utility, a utility compensated demand. However, it was criticised on the basis that the income is relatively volatile over the period of time, whereas, individuals smooth out their consumption over time. Friedman (1957) explained that it is the permanent income that matters for inter-temporal consumption. So, it has been argued that wealth should be considered, as being the present value of all the future incomes and present income. But, in this case collecting the information on a household's future income is more difficult than current consumption which is dependent on permanent income. Therefore, consumption is preferred both conceptually and practically over income. However, Deaton and Zaidi (2002) have shared a list of items to be excluded from a consumption aggregate: taxes and levies, expenses for own-account businesses, repayment of debt and interest, purchases of financial assets, remittances and transfers to other households, and infrequent items like funerals and dowries. For durable goods and houses, flow of services should be calculated.

In the capabilities approach, the debate in literature is over what dimensions for deprivation should be considered and how those dimensions should be aggregated. The work of Alkire (2002) describes the dimensions for human development and has identified a list of capabilities based on Sen (1980). Bourguignon and Chakravarty (2003) worked on finding interrelationships that existed in dimensions to be used for multidimensional poverty measures. The use of multidimensional poverty estimates in literature has shown growth over the last two decades. In academic literature, the work on axiomatic poverty measures can be found by

Anand and Sen (1997), Brandolini and D Alessio (2000), Chakravarty et al. (1998), Tsui (2002), Atkinson (1987), Bourguignon and Chakravarty (2003), Deutsch and Silber (2005), Duclos and Araar (2006), Chakravarty and D'Ambrosio (2006), Kakwani and Silber (2008), and Thorbecke (2008). However, Alkire and Foster (2011) identify three broad dimensions for poverty estimation: standard of living, education and health. However, Atkinson (2003) worked on finding the interrelationship between axiomatic multidimensional poverty measures and counting based poverty measures. But the debate on identifying what dimensions to use in poverty estimation still continues.

Third question. How should the poverty cut off point be set (the poverty line)? In the welfare-based poverty estimation, the income is regressed on welfare related characteristics. The characteristics usually involve nutritional status, food share or subjective welfare for each household or person. A specific level of welfare is set as a starting point. Then the estimated income at that level of welfare is considered as poverty line. Another method involves setting the level of utility to be identified as poor and then the Basic Need Bundle on that level of utility is selected. Once the Basic Need Bundle is selected, the cost to attain that bundle is set as poverty line.

Another approach in this regard is Food-Energy Intake (Osmani,1982). In this approach the nutritional/ energy level required for a healthy life is calculated first. The expenditure of the household / person satisfying that energy requirement is set as a poverty line. The execution of this method can be seen in the work of Greer and Thorbecke (1986), and Paul (1989). There is another approach in which an allowance for the cost of a food bundle is added to non-food expenditure for setting poverty line – this is named as the Engel Curve method. A practical example of the Engel curve is the US poverty line based on Orshansky's (1965) work which was criticized by Citro and Michael (1995) for the redundancy of a poverty line set over time and space. They introduced the idea of relativism in setting the poverty line for US by anchoring it to the current median of expenditure on food, clothing and shelter. In the Cost of Basic Need (CBN) methodology a combination of goods is considered for a healthy life usually in terms of consumption goods - their cost is calculated for setting poverty line .

Another debate arose on whether a poverty line should be relative or absolute. Scitovsky (1978) mentioned 'the minimum social standard of decency' in the connotation of relative poverty lines. It has been suggested in literature that relative poverty measurement is more relevant for developed countries (Townsend, 1985). Fuch (1967) introduced the method of setting poverty at 50 percent of median income/expenditure for relative poverty lines. Atkinson (1991) has done the sensitivity analysis of poverty to the different poverty line setting methodologies (in terms of relative or absolute) across countries. The relative poverty lines is criticised that if the income of all the individuals in the society increased by a fixed proportion then there would be no change in the poverty measure. Sen (1980) argued that poverty comparison should be absolute in terms of capabilities and relative in terms of functionings.

In the multidimensional poverty approach which arose from quantifying capabilities - counting based approach - different variables are considered for poverty estimations. Alkire and Foster (2011) identify three broad dimensions for poverty estimation: standard of living, education, and health using household level surveys to get maximum data from joint distributions; whereas Anand and Sen (1997) used different marginal distributions from different populations to calculate a poverty measure. Alkire and Foster (2011) argued that in their index as many dimensions can be added as wished however from the same data source (survey). The difference between old multidimensional poverty measures and Alkire and Foster is that the focus of old measures was more on aggregation methodologies than on identification. Whereas for Alkire and Foster (2011) identification is the most salient step in poverty estimation. Like

Tsui (2002), Chakarvarty and Silber (2008) identified non-linear aggregation for cardinal measure; Chakravarty and D Ambrosio (2006) identified ordinal non-additive measure; whereas Rippin (2010) was in favour of an additive cardinal and ordinal measure. It has been claimed that Alkire and Foster's poverty index is based on an axiomatic framework which is then criticized by Datt (2017) noting the violation of strict transfer and redistribution axiom.

Fourth question: What poverty index should be used for poverty estimation? A list of axioms can be found in literature which must be complied to create a comprehensive and comparable poverty measure. Zheng (1993) presented a list of axioms which a good poverty measure should possess. Focus axiom requires the poverty measure to be unaffected by the changes in poverty related variables of the non-poor class. A monotonicity axiom requires the poverty measure to increase with the drop in income of poor. An extension to this is a subgroup monotonicity which requires that if the income of poor from a subgroup drops the overall poverty should increase. An additive axiom requires that a poverty estimate for the whole population should be sum of poverty estimate of subgroups. Poverty estimate should be unchanged if the income and the poverty line change by the same proportion (the measure will be called homogeneous of zero degree). For replication invariance the poverty estimate should remain the same for two identical populations. The transfer axiom requires a poverty estimate to drop when a transfer is made from a poor person to a poorer person (without changing their relative position). The redistributive transfer axiom requires the poverty estimate to increase if transfer is made from poorer person to a relatively less poor person in a way that transferee, after the transfer, move out of poverty.

The Head count index which is the proportion of people living below poverty line is easy to interpret but does not satisfy monotonicity, transfer and redistribution axioms. The poverty gap (PG) index, averages proportional gap from poverty line (if income is greater than poverty line, it is set to zero). It does not satisfy the transfer axiom. The income gap ratio; the average distance of only poor population from the poverty line as a proportion of poverty line does not satisfy monotonicity and transfer axioms. For the squared poverty gap (SPG) index proposed by Foster et al. (1984), the whole PG index is squared to give more weight to the most aggrieved before averaging, this index satisfies transfer and redistribution axioms as well. The Watts index proposed by Watts (1968) is the mean proportionate gap but the difference is in log, and considering the non-poor as having zero gap, this index satisfies all the axioms mentioned by Zheng (1993). The comprehensive index developed by Foster Greer and Thorbecke (FGT) can take any form depending on the value taken by alpha. Like for $\alpha = 0$ FGT is headcount Index, $\alpha = 1$ is PG and $\alpha = 2$ is SPG.

$$\text{FGT} = P_\alpha = \frac{1}{n} \sum_{i=1}^{n} (1 - \frac{y_i}{z})^\alpha$$

In counting-based multidimensional poverty measures, the MPI introduced by Alkire and Foster (2011), satisfy most axioms like, focus, monotonicity and weak transfer. However like SPG, the multidimensional index introduced by Datt (2019) satisfies the additional axioms of strict transfer and redistribution. The detailed discussion on the indices is in chapter four.

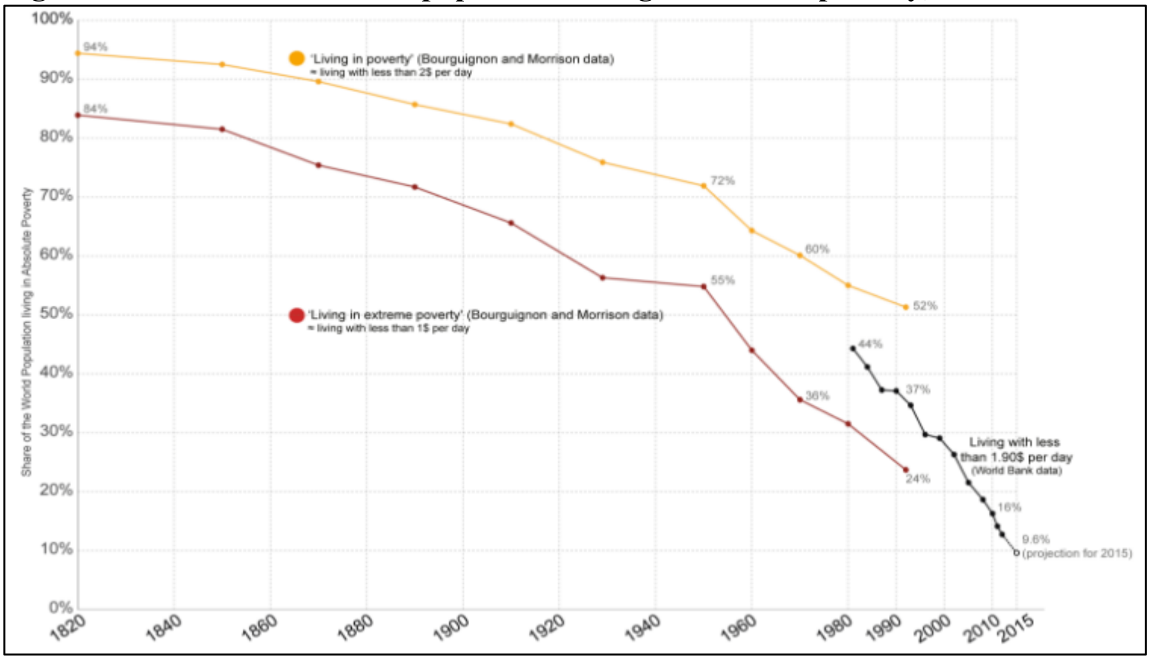
Going through the history of poverty measures highlights the similarities in the evolution process which exists in those two streams: conventional and non-conventional poverty measures. Both types of measures have same four questions and the debate in literature to answer those questions is also similar. The debate for both the measures in finalising the welfare variables is similar. In conventional measures it is mostly either consumption or income whereas for non-conventional measures it is around what dimensions to use. There is also similarity in setting the poverty cut-offs for conventional and non-conventional poverty measures. More so the increased interest is in indices which satisfies the axiom of distribution sensitivity for both conventional and non-conventional poverty measures.

2.3 World in Poverty

The need for a poverty estimate is indispensable if the well-being of a society is to be studied. Poverty estimates have been used for comparison purposes across and within economies. For this purpose, World Bank (WB) is publishing conventional poverty estimates for the world on annual basis. In 1990, after Sen (1980) presented the idea of capability approach; the first Human Development Report was introduced with a composite index, the Human Development Index (HDI). It is used for assessing achievements in the basic dimensions of human development. For HDI, the dimension of living a long and healthy life is measured by life expectancy at birth; the dimension of acquiring knowledge is measured by mean years of schooling and expected years of schooling; and the dimension of achieving a decent standard of living is measured by gross national income per capita. These dimensions are calculated using macro-level data. Since 1990, HDI is reported on an annual basis to give a snapshot of economies on dimensions of development noted above. Then, during 2007, Alkire and Foster (2007) introduced a multidimensional poverty index in their Oxford Poverty & Human Development Initiative working paper which took into the account the same kind of the dimensions as those used in HDI albeit at micro-level, using household level surveys to present the snapshot of economies and to develop a comparison.

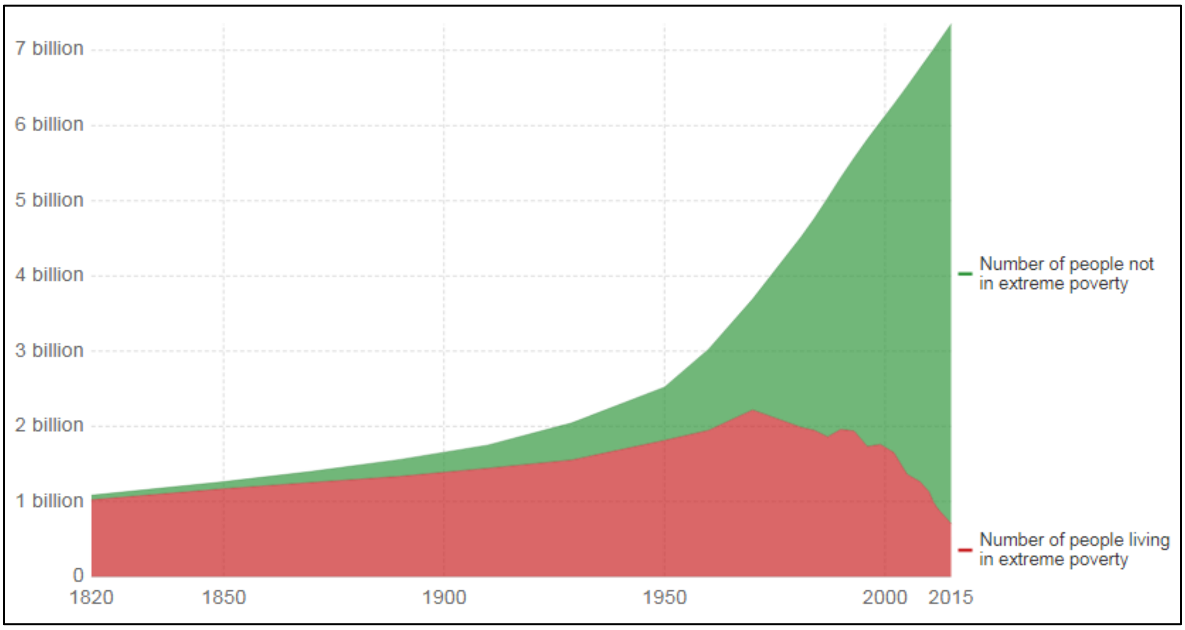
The figure 2.1 shows the movement of conventional, money-metric poverty estimate for the world which is declining since 1820. However, the rate is faster post 1960.

Figure 2.1: Share of the world population living in absolute poverty, 1820-2015



Source: (Our World in Data, 2019)

Figure 2.2: World population living in extreme poverty (absolute numbers), 1820-2015

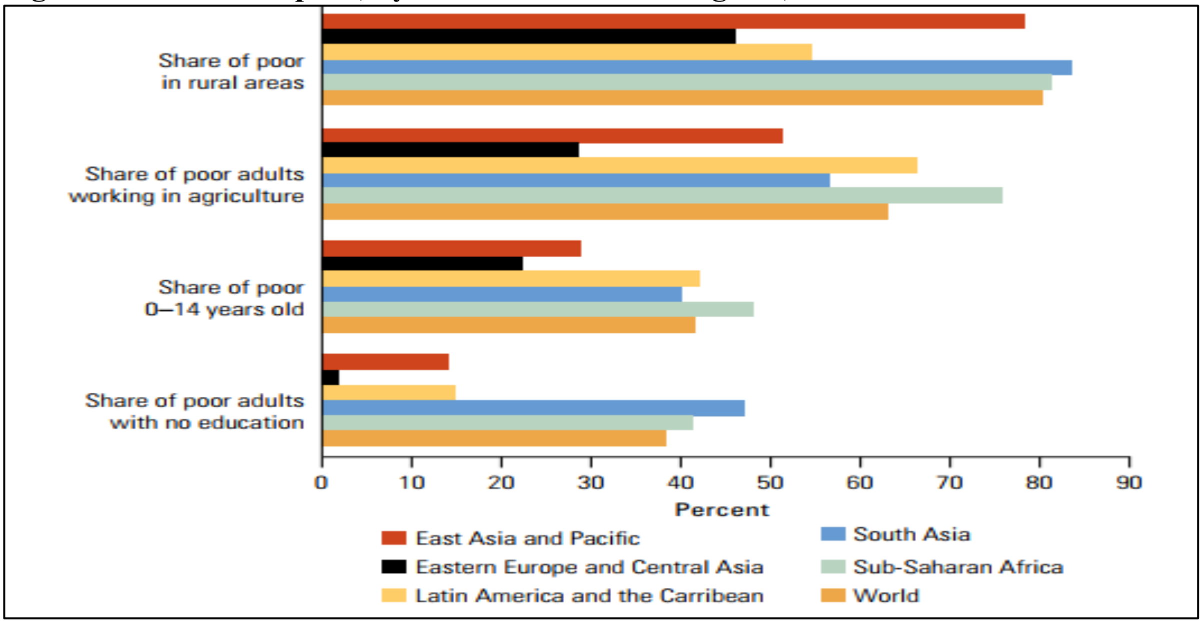


Source: (Roser & Ortiz-Ospina, 2013)

The trend in absolute poverty from 1820 – 2015 is shown in the figures 2.1 and 2.2 using the poverty line set by WB. A sharp decline in extreme poverty can be seen post 2000 with the share of people living in extreme poverty substantially reduced (see Figure 2.2).

The demographic profile of the poor at the US$ 1.90 poverty line using a large database of household surveys in 89 developing countries provides insights into the characteristics of poor (World Bank, 2016). The poverty profile shown in Figure 2.3 shows that the global poor ($1.90/day) are predominantly rural, young, poorly educated, mostly employed in the agricultural sector, and live in larger households with more children. Worldwide, 80 percent of the poor live in rural areas; 64 percent work in agriculture; 44 percent are 14 years old or younger; and 39 percent have no formal education at all. By looking at the figure 2.3 it can be seen that for South Asia special attention is required for rural poverty.

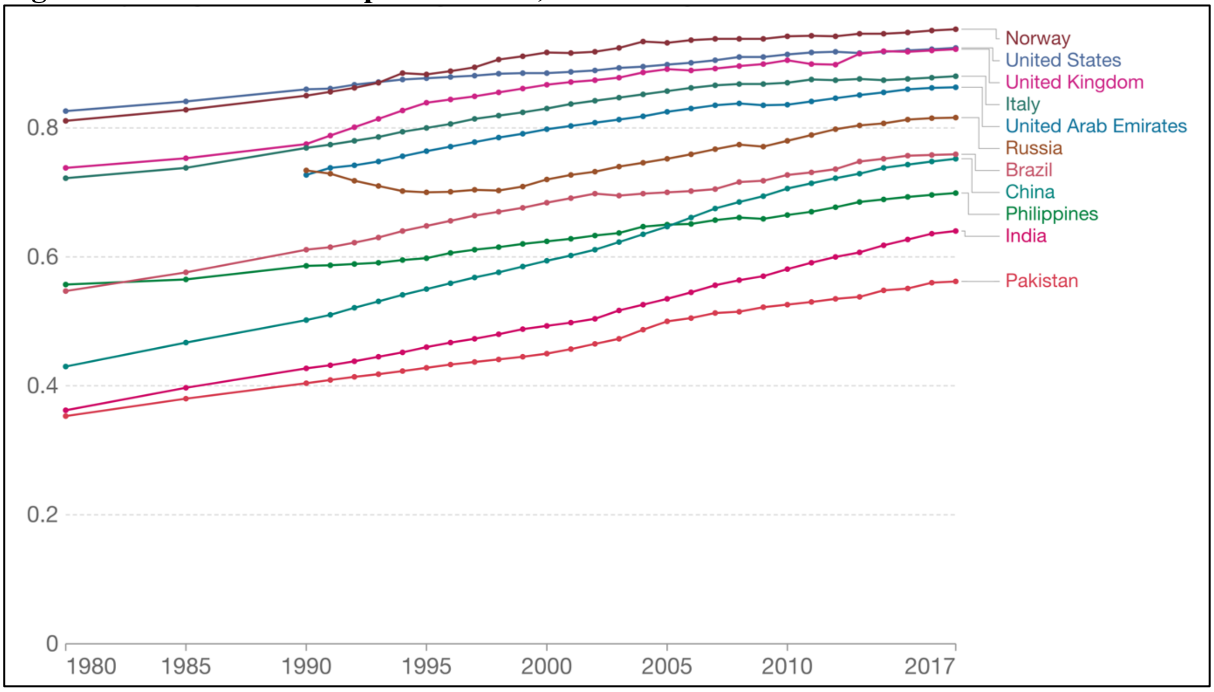
Figure 2.3: Profile of poor, by characteristics and regions, 2013



Source: (World Bank, 2016)

Not only the absolute poverty has decreased over years but also HDI has improved in all regions of the world. Between 1990 and 2015, the aggregate HDI value of the least developed countries increased 46 percent, and the aggregate HDI value for low human development countries increased 40 percent. However, the progress in HDI post-2005 has been slowing down (see Figure 2.4). However, on contrary, there was a sharp decline in headcount index during this period.

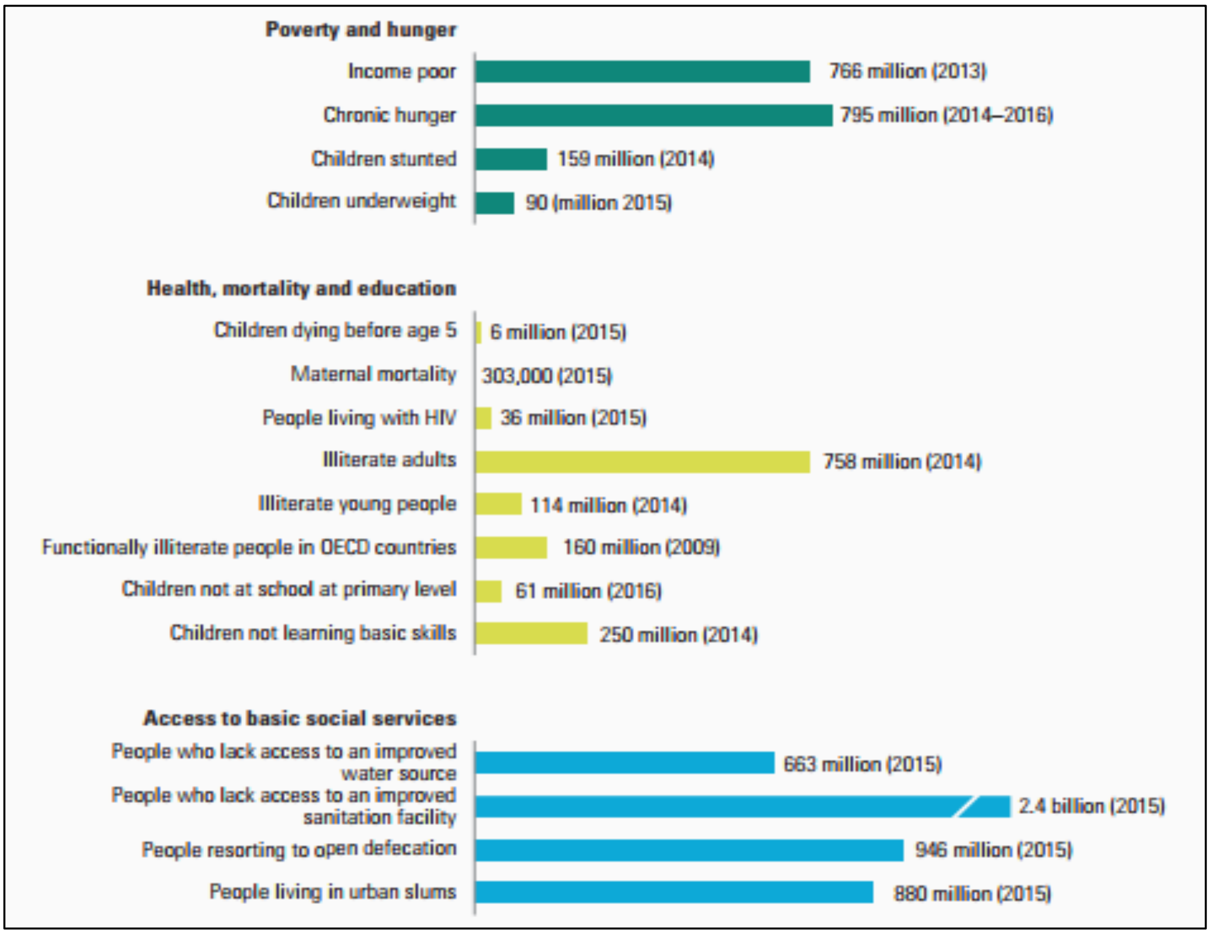
Figure 2.4: Human Development Index, 1990-2017



Source: (Roser, 2019)

The dimensions used in the calculation of HDI reveal mixed progress over time. The state of HDI dimensions updated by UNDP in 2016 can be seen from Figure 2.5. The global population has increased by 2 billion (from 5.3 billion in 1990 to 7.3 billion in 2015); more than 1 billion people escaped extreme poverty; 2.1 billion people gained access to improved sanitation, and more than 2.6 billion gained access to an improved source of drinking water. The under-five mortality rate has more than halved between 1990 and 2015, from 91 per 1,000 live births to 43. The incidence of HIV, malaria and tuberculosis declined between 2000 and 2015. However, there are some dimensions of well-being in which human deprivations lingers.

Figure 2.5: The state of dimensions / characteristics used in calculation of HDI

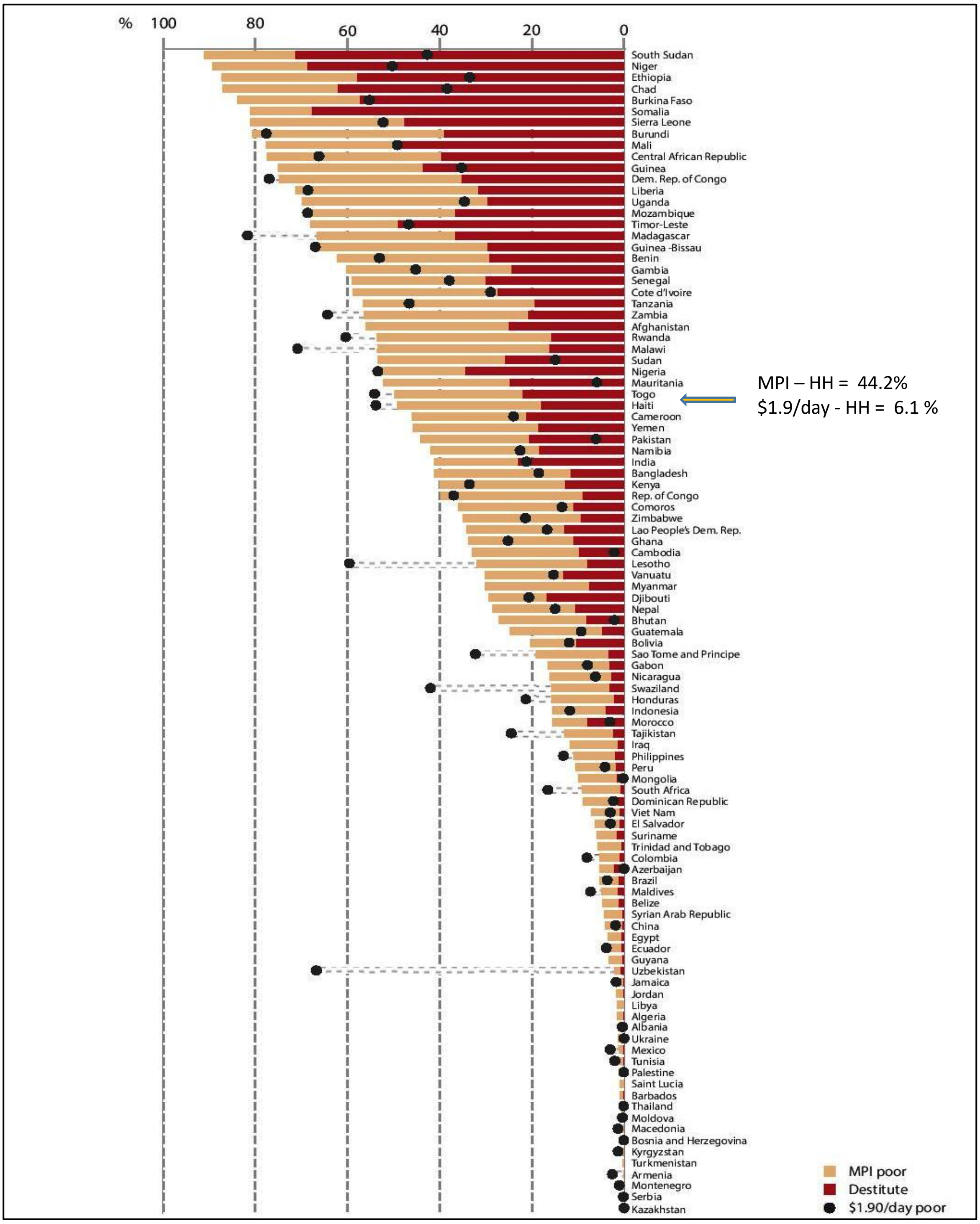


Source: UNDP (2016)

Observing differing progress in terms of human development and income/consumption status (see Figure 2.6), OPHI has compared the headcount ratios of MPI poor, $1.90/day poor, and destitute (extreme version of MPI, with more weights to certain extreme dimensions, for detail see Alkire & Robles (2017)).

The figure 2.6 shows a mixed outlook for poverty. In some countries the estimate for MPI poor is more than $1.90/day poor, and opposite in other countries. Calculating the Spearman correlation and the Pearson correlation, 0.34 and 0.33 respectively, do not show any strong correlation between these two poverty estimates. One thing to highlight at this stage is that these poverty measures, MPI and Headcount Index, satisfy different axioms which may make this comparison unreliable. Also the comparison shows a level effect for a particular point in time. A comparison over time, a trend analysis of these poverty measures, in particular those which satisfy same poverty axioms will be more explanatory and hence the need of the present research to contribute to the literature.

Figure 2.6: Comparing the headcount ratios of MPI poor, destitute, and $1.90/day poor



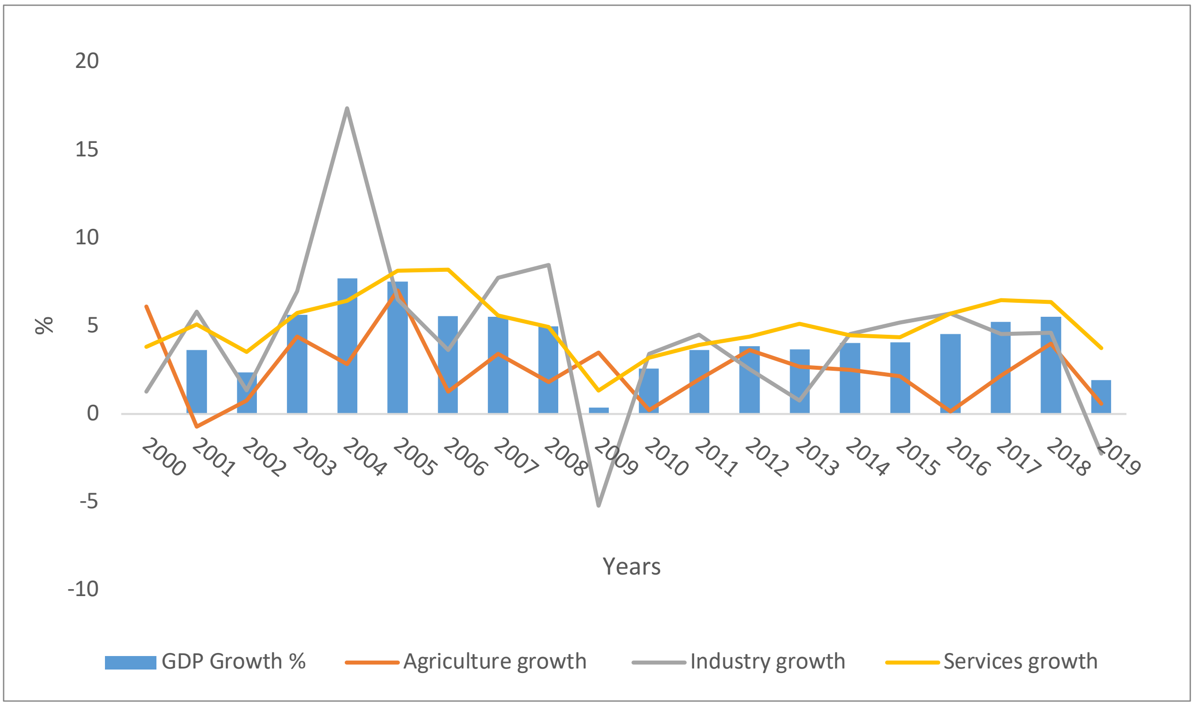
Source: Alkire and Robles (2017)

CHAPTER 3

Economic Snapshot of Pakistan

Pakistan, a 73 year old developing country with 187 million people, has around 50 million people living below national poverty line in 2015 (World Bank, 2020). Looking at the demographic distribution, around 57 percent of total population lives in rural areas. The rural population is mainly reliant on agriculture income. However, just 20 percent of GDP comes from agriculture sector. This means that the rural populations are not substantially gaining from the growth in GDP. In recent years, agriculture growth has been hindered by the climate change, like flooding in the country. This upheaval in agriculture sector is adversely affecting the poor population, which is reliant on agriculture income. There is instability in the GDP growth rate (see Figure 3.1). The growth in Pakistan is subject to political and environmental instability, a little disturbance in either disturbs the growth trajectory. This causes stress on the national exchequer.

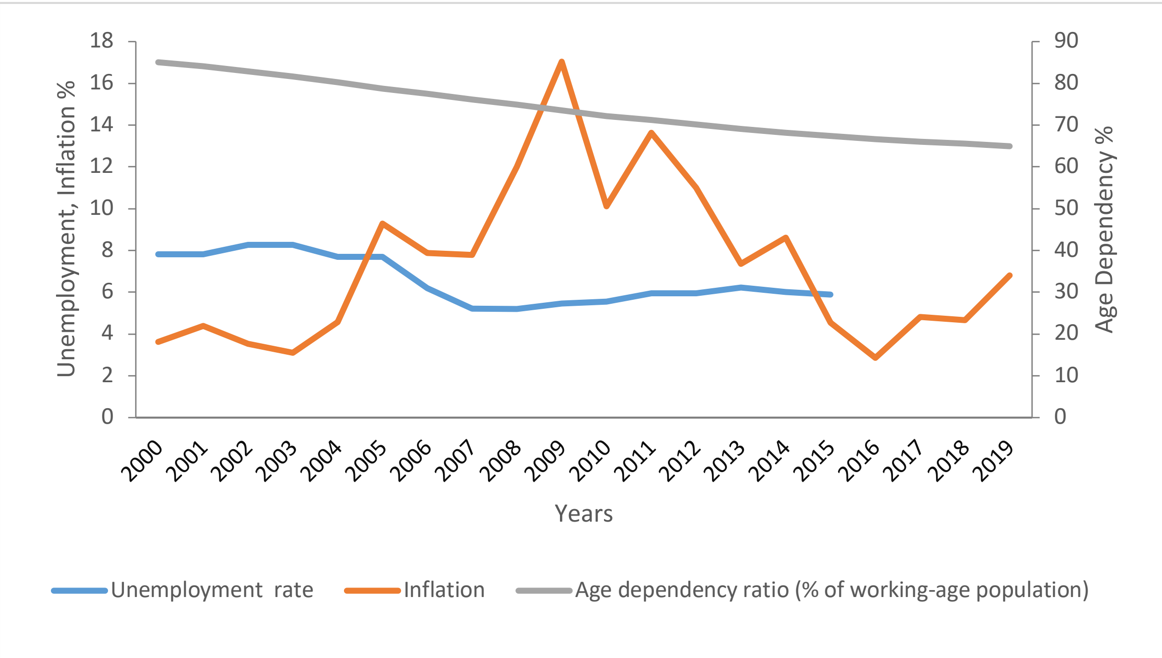
Figure 3.1: National and sectoral GDP growth rate (2000 – 2019)



Source: Government of Pakistan (2020)

The GDP growth in Pakistan is not promising along with this it experience high rate of inflation. The lower level of GDP growth puts constraints on the future level of production which, when coupled with high inflation, is deteriorating the vulnerable segment of the society. Even the increasing unemployment rate post 2007 in the economy is a sign of concern for anti-poverty programmes (see Figure 3.2). However, the reduction in age dependency rate is an indication of potential growth which Pakistan can capitalise on if appropriate intervention polices for specific regions are devised.

Figure 3.2: Unemployment rate, inflation, and age dependency rate (2000 – 2019)

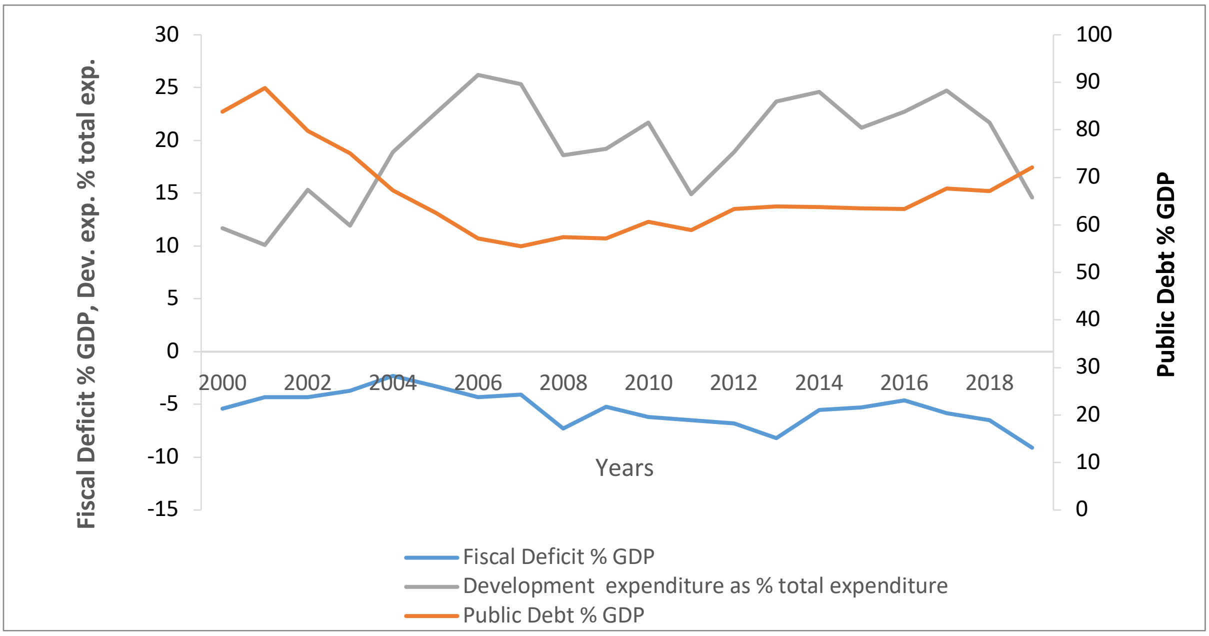


Source: Government of Pakistan (2020)

In midst growth and inflation volatility, government grapples with a soaring fiscal deficit. Pakistan total public debt was recorded at Rs 35,207 billion at end March 2020 which put constraints on development spending (see Figure 3.3).

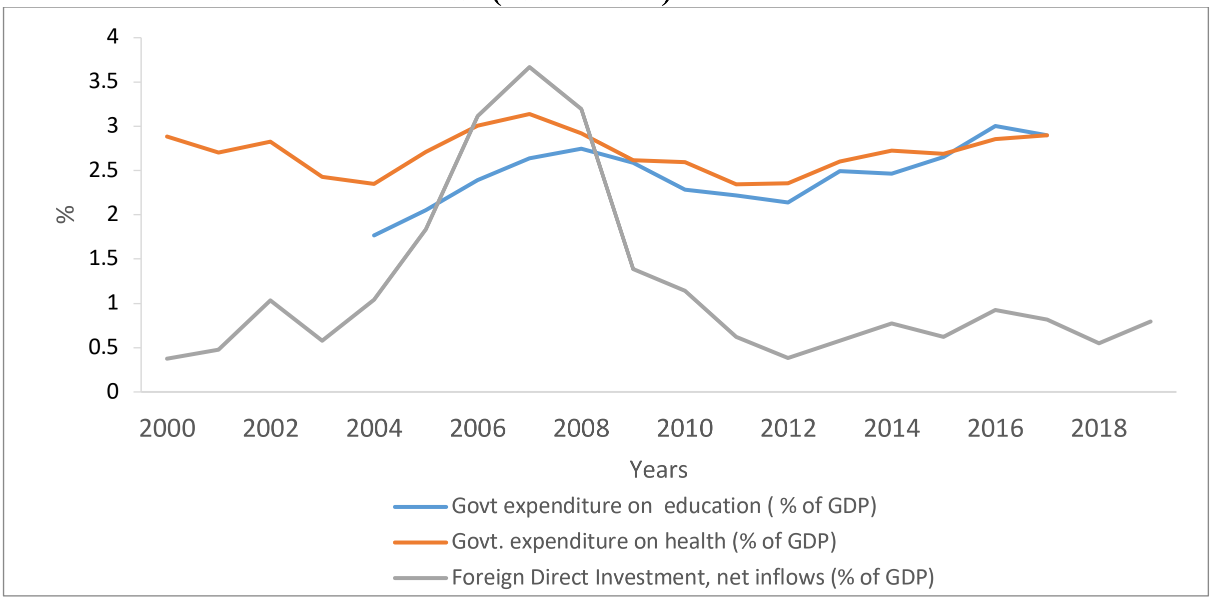
The IMF programme has restrictions for maintaining fiscal deficit at 2.5 percent of GDP down from 9.1 percent in 2018-19 (Government of Pakistan, 2020). This makes it more difficult for the government to increase development spending. Further, it adversely affects wide scale social safety net programmes. The government expenditure on education and health as a percentage of GDP does not show any substantial growth since 2008 (see Figure 3.4).

Figure 3.3: Fiscal deficit, development expenditure and public debt as percentage of GDP (2000 – 2019)



Source: Government of Pakistan (2020)

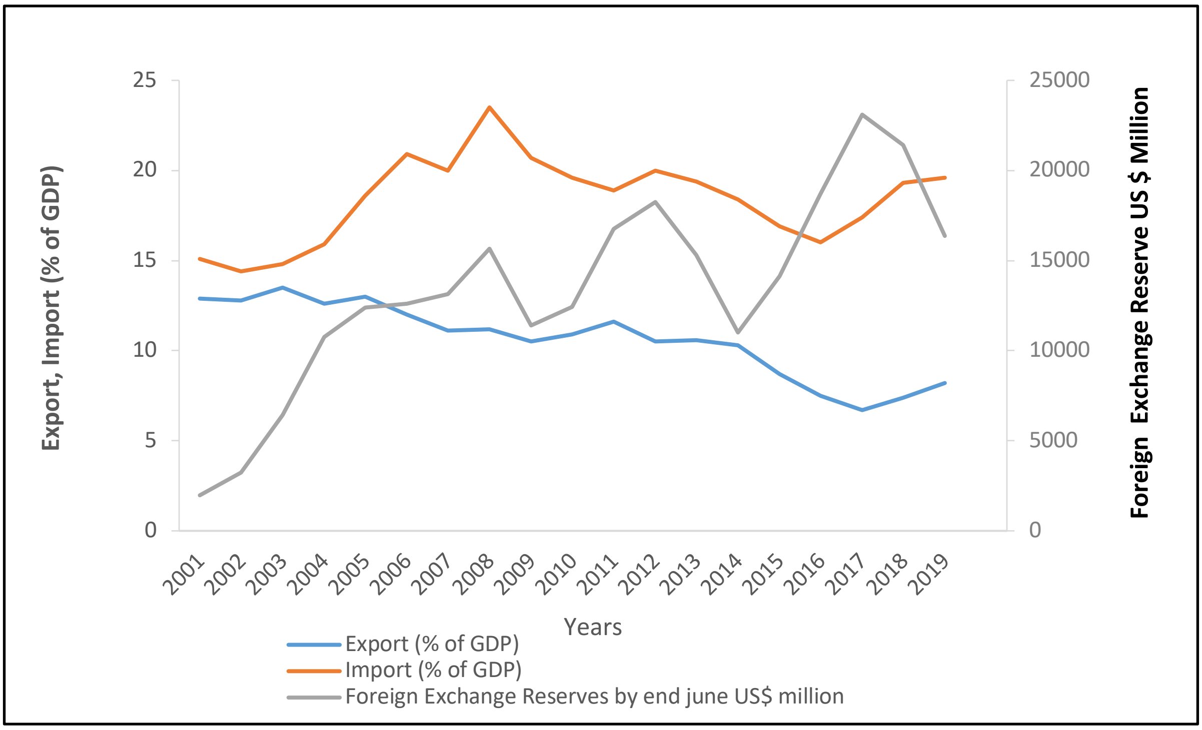
Figure 3.4: Government expenditure on education and health, Foreign Direct Investment net inflows (2000 – 2019)



Source: Government of Pakistan (2020)

Not only the internal economic situation of Pakistan is concerning but also the trade situation is not supporting the economy to flourish (see Figure 3.5). Pakistan has been struggling with maintaining the foreign exchange reserves which keeps on pushing it into the vicious cycle of external debt.

Figure 3.5: Export and import as a percentage of GDP, Foreign exchange reserves by end of June (2000 – 2019)



Source: Government of Pakistan (2020)

Pakistan is facing two-sided sword; insufficient growth due to political and environmental factors, and increasing fiscal deficit. Each side has depressing consequences for poor due to scarce financial and developmental support. In the midst of the tight financial and economic situation, Pakistan has continued its social protection programmes. With its limited financial and institutional capacity, those programmes have had little known or discernible impact (Khan & Qutub, 2010). There were two broad categories of social protection programmes prior to Benazir Income Support Programme. The first one, introduced in 1950s, has been engulfed by the employees' social security scheme, the old age benefits institution, and the workers' welfare fund. Those were targeted towards people employed in the formal sector, retired labour force (excluding agricultural and informal sector labour forces). The second category is based on cash assistance programmes, such as Zakat, Pakistan Bait-ul-Mal and various public works programmes. World Bank (2007) noted that the low budgets, design and implementation errors were the basis of their falling short of targets and their minimal impact. Benazir Income Support Programme which began in 2008 has gained attention, and its targeting performance was ranked in the world's top five Social Safety Net programmes (World Bank, 2015).

As this study is focused on district-level analysis, a brief overview of Pakistan's geography is presented ahead. Geographically, Pakistan has four provinces Balochistan, Sindh, Khyber Pakhtunkhwa and Punjab, and two federally administered areas Gigit-Baltistan and Federally Administered Tribal Areas as of 2004 (see Figure 3.6).

Balochistan is endowed with natural resources: coal, gas, gold, copper and many more. It also has a natural deep-sea port where the China-Pakistan Economic corridor crosses. This is the least populated but largest in terms of area. Although it is endowed with natural resources it has the highest illiteracy, poverty, and dearth of infrastructure development. Unfortunately, Pakistan could not make use of those natural resources to optimum due to capacity and financial constraints.

Sindh, has the oldest civilization, and its poor people, are reliant on livestock and agriculture income. Their source of income is subject to global warming, they are either experiencing droughts or heavy flooding.

Khyber Pakhtunkhwa known for its scenic beauty, attraction for tourists, has highest literacy rate in all four provinces. However, Khyber Pakhtunkhwa has been subjected to security issues because of terrorism which has affected the socio-economic growth of the province.

Punjab, which is the largest province in terms of population, has a poor population mostly clustered in its south where infrastructure development needs attention. Pakistan has a complex geopolitical positioning in the world. However, this should not divert the attention from a destitute and deprived population suffering from political and economic havoc. The narrative of World Bank on Pakistan is: "Pakistan has important strategic endowments and development potential. The increasing proportion of Pakistan's youth provides the country with a potential demographic dividend and a challenge to provide adequate services and employment."[3] Region specific policy interventions can help Pakistan capitalise on its resources and fight poverty. Few high-level provincial statistics for 2014-15 are presented below in the table 3.1.

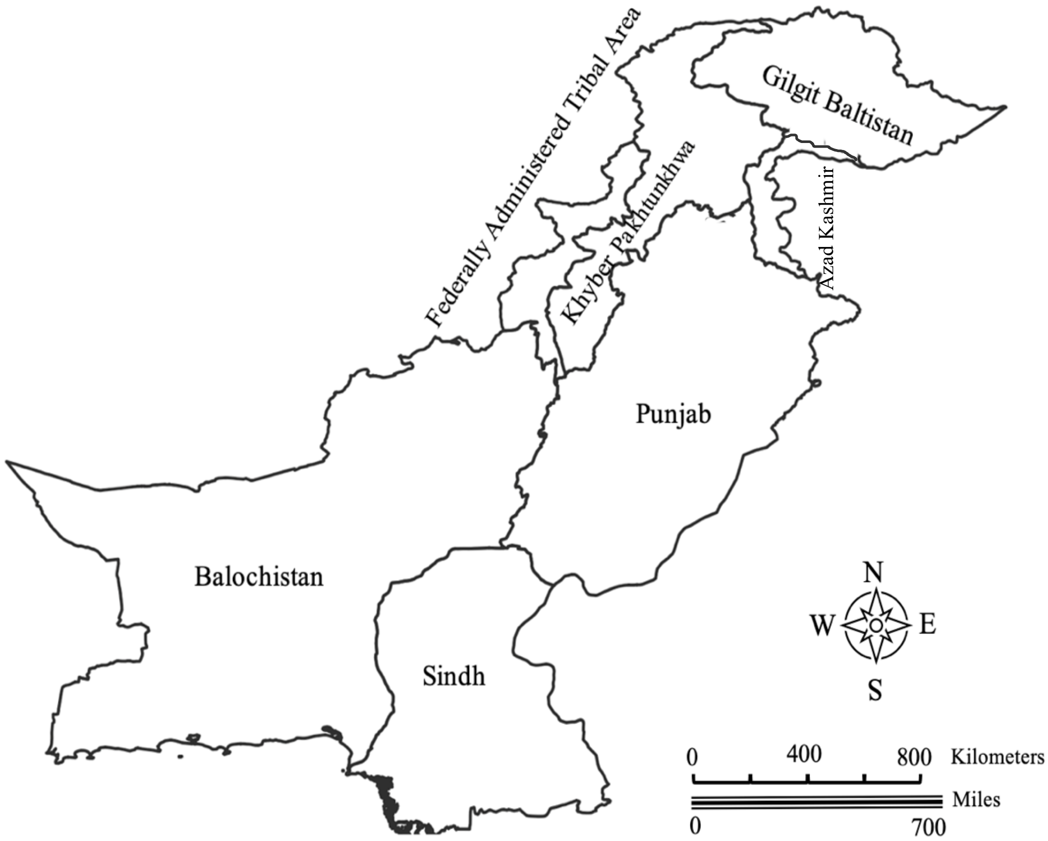
Table 3.1: Provincial statistics of Pakistan

Provinces	Population (million)	GDP (at constant prices of 2005-06 billion Rs)	GDP Share (%)	Human Development Index (2015-16)	Agriculture contribution (2012-13)	Industry contribution (2012-13)	Services contribution (2012-13)
Punjab	105.30	5757.0	54.1	0.574	62.3	39.8	55.7
Sindh	45.99	3192.5	30.0	0.572	23.1	42.2	28.9
Khyber Pakhtunkhwa	25.8	1380.9	13.0	0.546	10.5	14.2	13.0
Balochistan	10	313.7	2.9	0.473	4.1	3.8	2.4
Pakistan	187	106441.1	100	0.536	100	100	100

Source: Pasha (2015 & 2019)

[3] https://www.worldbank.org/en/country/pakistan/overview

Figure 3.6: Provincial map of Pakistan



Source: WorldmapBlank.com

CHAPTER 4[4]

The Sensitivity of Poverty Trends to Dimensionality and Distribution Sensitivity in Poverty Measures – District Level Analysis for Pakistan

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Abstract

A key feature of recent poverty measurement in many developing countries is the transition from conventional (money metric) approaches to multi-dimensional approaches. This change in the poverty measurement raises the question of whether the same poverty trends are apparent under the conventional and the multidimensional approaches. To answer this question I used six household level surveys for Pakistan fielded between 2004 and 2015. The analysis considers trends at the national, provincial, and district-level with a particular focus on the variability in trends due to distribution sensitivity and insensitive in poverty measures. The district-level trend analysis leads to the results that the multidimensional measures show a smoother fall in national poverty rates while the conventional measures show rising poverty up until 2008 and then a sharper fall. Almost two-third of all districts show opposite trends in poverty, if conventional rather than multidimensional measures are used, in at least two of the five inter-survey spells, irrespective of whether distribution-sensitivity is considered or not. Thus, apparent poverty trends are sensitive to the measurement approach used. Hence, when measurement methods evolve, policy analysts should be cautious in the conclusions they draw from poverty estimates.

Keywords: Multidimensional poverty index, distribution sensitivity, poverty trends
JEL Codes: I32

ABBREVIATIONS

HIES: Household Income Expenditure Survey
HH: Headcount Index
MPI-HH: Multidimensional Headcount Index (Alkire and Foster)
MDPI-HH: Multidimensional Distributionally Sensitive Headcount Index
MPI: Multidimensional Poverty Index (Alkire and Foster)
MDPI: Multidimensional Distributionally Sensitive Poverty Index
PG: Poverty Gap
PSLM: Pakistan Social and Living Standards Measurement Survey
SPG: Squared Poverty Gap
SAE: Small Area Estimation

4.1 Introduction

The first goal set by the United Nations under the Sustainable Development Goals is to "End extreme poverty in all forms by 2030" (United Nations, 2015). Given this goal, there has been a great interest in estimating poverty trends at the national and sub-national level in order to ascertain how well the countries and regions are tracking towards this goal. A growing feature of these poverty estimates is the use of multidimensional poverty indices, either to replace or supplement conventional (money metric) poverty measures. This trend of using multidimensional indices can be traced to the start of the century when the *Human Development Report* (UNDP, 2010) included multidimensional measures of poverty which are derived from the work of Sen (1980, 1992, 1997, 1999, 2010).

The transition from one measurement approach to another is plausible when the new and advanced technique is more explanatory and non-contradictory in term of its results. Hence in the current research the question of whether the two approaches reveal the same trends, in terms of progress towards meeting the SDGs is investigated. One may hope that the trends are the same, given that both conventional (money metric) and non-conventional (multidimensional) poverty measures encounter common problems in defining and measuring poverty (Laderchi, Saith & Stewart, 2003). For example the debate over setting poverty thresholds and the selection of welfare proxies is similar. For the poverty threshold: with conventional measures, the debate is on setting the poverty line, whereas with non-conventional measures, the debate is on setting the poverty cut-off on the dimensions used. Likewise, for the welfare proxies: with conventional poverty measures, the debate is on the choice of either consumption or income, whereas for non-conventional measures, the debate is on the choice of welfare dimensions to be considered in the calculations.

There is another commonality between both the approaches (the conventional and the multidimensional). They both have shown a pattern whereby when a new poverty measure is introduced it typically claims compliance with more axioms. Amongst these axioms, greatest importance is attached to the transfer axiom and redistribution axiom (distribution-sensitivity). This is the axiom which I will also be focusing on in the poverty measures while conducting poverty trend analysis. This distribution-sensitivity means that the poverty measure is convex in deprivations.[5] Thus, it requires the poverty measure to increase if a transfer is made from a poorer person to a relatively less poor person. In distribution-sensitive measures, more weight is given to the individual in poverty estimation if he/she is deprived in more dimensions or is farthest from the poverty line. Specifically, conventional poverty measures evolved from distribution-insensitive measures (Head count Index, Income Gap, Poverty Gap) to then also include distribution-sensitive poverty measures (Squared Poverty Gap, Watt Index, Average Exit Time). The same evolution can be seen in multidimensional poverty measures (based on the counting tradition) starting with the distribution-insensitive, Alkire and Foster (2011) MPI and then evolving to include the distribution-sensitive poverty measure, Datt (2019) MDPI.

Given the upsurge in the use of non-conventional poverty measures, some researches have already been conducted to study the overlap in identifying the poor, and whether there is over-or-under estimation of poverty in a particular point in time, when using either conventional or multidimensional measures (Azeem et al., 2018; Kwadzo, 2015; and Bhusal, 2012). However, firstly, the issue of whether the temporal trends in poverty estimates coming from the multidimensional approach compared with those coming from the conventional approach is neglected in the literature. Secondly, another issue with existing studies is that the comparisons

[5] For more detail on poverty axioms see Zheng (1993)

made were not cognizant of the various axioms those poverty measures satisfy. For example, if a comparison is conducted between poverty measures where one satisfies the monotonicity axiom and the other does not, then the results of the comparison may be questionable. Moreover, the comparisons made to date do not consider the sensitivity of poverty estimates to redistribution axiom. Therefore, the present study attempts to provide evidence for these two gaps in the literature.

Specifically, this study examines whether the same temporal trends in poverty are apparent when an analysis uses either the conventional or the multidimensional approach in estimating distribution sensitive and distribution insensitive poverty measures. The research context of this study is Pakistan, where the poverty rate seems to have fallen rapidly in the past two decades, going from two-thirds of the population living under the nationally defined poverty line in 2000 to just one-quarter below the line in 2015 (World Bank, 2020). These measurements by the World Bank are based on a conventional poverty measure, the Headcount Index. Despite this progress, almost 50 million people were still living under the national poverty line in 2015. Also, the progress at the national level has not been repeated equally in all parts of the country (Iqbal, 2020 and Government of Pakistan, 2020). Therefore, this research examines the poverty trends for the period of 10 years (2004–2014) at national, provincial and district-level using both conventional and multidimensional poverty measures while also considering the effects of allowing for distribution-sensitivity (which has previously been ignored by other comparative studies). The motivation for carrying out the analysis at three different spatial levels is because of the importance highlighted in literature of calculating poverty estimates at the disaggregated levels for effective policy interventions in eradicating poverty (Gibson et al., 2005). Likewise, having reliable information on poverty trends at disaggregated level helps in devising effective poverty eradicating initiatives (Banerjee & Duflo, 2011).

In the results presented below, the multidimensional measures show a declining trend in national poverty rates while the conventional measures showing temporal fluctuations. Specifically, the conventional poverty measures show an increasing trend up until 2008 which starts to decline thereafter. Sub-nationally, almost two-third of all districts show opposite poverty trends, in at least two out of the five inter-survey spells, if conventional rather than multidimensional measures are used. The sensitivity of poverty trends is irrespective of whether distribution-sensitivity is considered or not. As the trends appear to be sensitive to the poverty measurement approach used, policy analysts need to be careful when drawing conclusions from the poverty estimates, especially when poverty measurement approaches evolve and multidimensional measures either supplement or supplant conventional ones.

The analysis relies on the data from the Pakistan Social and Living Standards Measurement (PSLM) surveys and the Household Income and Expenditure Surveys (HIES), which were fielded in alternate years from 2004-05 to 2014-15. The combination of these two data sources allows me to measure poverty at national, provincial and district-level for six different periods. In the conventional poverty measures: the Head Count, Poverty Gap (distribution-insensitive) and Squared Poverty Gap (distribution-sensitive) indicators are estimated. In the non-conventional measures, the Multidimensional Poverty Index which was introduced by Alkire and Foster (2011) and the Multidimensional Distribution-sensitive Poverty Index which was introduced by Datt (2019) are estimated. The poverty estimates using these measures are calculated for each of six years, 2004, 2006, 2008, 2010, 2012 & 2014, generating five spells between the surveys.

4.2 Analytical Framework

The deprivation in the welfare of individuals is usually measured either by conventional money metric poverty measures or non-conventional multidimensional poverty measures. These poverty measures have evolved over time, by complying to the increased number of axioms like focus axiom, monotonicity axiom, transfer axiom, and redistribution axiom. Given the evolution in these poverty measures is in the same direction, (for example, development of distribution-sensitive measures) this has attracted the interest of various researchers in studying the overlap in poverty estimates calculated using these measures. For example, Laderchi *et. al.,* (2003) conducted an empirical analysis for India and Peru which showed significant lack of overlap between the headcount Index (HH) and Human Poverty Index (HPI), where the HPI is a multidimensional index. Note that in this study the Headcount Index is calculated at household level whereas the Human Poverty Index is calculated at the aggregated level. A study by Azeem et al. (2018) on the Punjab province of Pakistan for 2011 showed non-overlapping identification of the poor using the Headcount Index versus using the Multidimensional Poverty Index (MPI). Note that in their study the comparison is made between a conventional poverty measure (Headcount Index) which does not satisfy the monotonicity axiom and a non-conventional measure (MPI) which does satisfy. Related studies include Kwadzo (2015) for the USA, who showed varied proportions of the poor identified using Headcount compared to an education indicator under the capability poverty measure for 2004. Bhusal (2012) for the Nepal showed underestimation of money-metric poverty measure as compared to multidimensional poverty measure (MPI) for 2010.

The examples I have provided from the literature suggest that conventional and non-conventional poverty measures give different estimates and identification of poverty for a given point in time. This is perhaps not surprising because the non-conventional poverty measures cater for a vast range of factors whereas the conventional approach just caters for one factor: consumption or income. However, this should be a level effect rather than something that affects time trends, so it is crucial to research whether the poverty trends of these measures are identical or not. Also, the analysis is designed in a way that the comparisons are made between poverty indices which satisfy the same poverty axioms. Hence, in this research poverty measures are classified into two categories conventional and non-conventional. These are further sub categorised based on their relevance to the axioms. The sub-categories are distribution-insensitive measures and distribution-sensitive measures. The poverty measures which are convex in deprivations satisfies the axiom of distribution sensitivity and falls under the distribution-sensitive measures. The classification can be shown in a 2 x 2 matrix.

Poverty Measures	**Conventional**	**Non-conventional**
Distribution-insensitive	Headcount Index (HH) Poverty Gap index (PG)	Alkire and Foster (2011) Multidimensional Poverty Index (MPI)
Distribution-sensitive	Squared Poverty Gap Index (SPG)	Datt (2019) Multidimensional distribution- sensitive Poverty Index MDPI

Therefore, in this paper the focus is on researching whether the same trends in poverty are apparent under the money-metric poverty measures and the multidimensional poverty measures which are *distribution insensitive*. The same trend comparison is conducted between money-metric and multidimensional poverty measures which are *distribution sensitive*. This trend comparison is conducted at the national, provincial and district-level of Pakistan.

4.3 Data

There are two sources of data used for the analysis. The first is the PSLM (Pakistan Social and Living Standards Measurement Survey); a multi-topic survey that is representative at national, provincial (n=4), and district-level (n=100 districts). Information on topics such as education, health, fertility, and access to basic services is gathered by the PSLM but it does not gather expenditure or consumption data. Consequently, the PSLM is used in Pakistan to calculate non-conventional (multi-dimensional) poverty indices but not any monetary-based conventional measures. Instead, monetary-based measures come from the Household Income and Expenditure Survey (HIES), which collects information on household income, savings, liabilities, and consumption expenditures, for a sample about one-fifth as large as the PSLM sample (see Table 1). Consequently, the only published conventional, money-metric indicators of poverty, distribution sensitive and insensitive are for the national and provincial level.

In order to create a district-level database (panel) of both conventional and multidimensional poverty measures, I use survey-to-survey imputation based on the Small Area Estimation (SAE) method of Elbers et al. (2003). This enables imputed values of consumption to be developed for all households in the PSLM samples, so that both multidimensional and conventional money-metric poverty measures can be calculated at the district-level. Details of the SAE procedure are explained in the subsequent section but a point to immediately note is that the PSLM and HIES surveys either overlap in time or are from nearby months, improving imputation quality (see Table 1). Also, as demarcation of districts changed over the last 15 years, the geography of districts as it was in 2004 is used for the analysis. Typically this means that districts that have subsequently been split off from their parent district are refolded back into that parent district to give a consistent set of spatial units from 2004 to 2014. The details on the concordances to create this consistent geography are provided in Appendix A.

Table 1: Survey Details and R Sq of Beta Model (Rural and Urban) from SAE for all six years

Years	Surveys	Survey Period	Sample Size			R sq. Beta model	
			Total	Urban	Rural	Rural	Urban
2004-05	PSLM	Sep 04 - Mar 05	76520	27144	49376	45%	67%
	HIES	Jul 04 - Jun 05	14673	5794	8879		
2005-06	PSLM						
	HIES	Jul 05 - Jun 06	15453	6240	9213		
2006-07	PSLM	Oct 06 -May 07	73953	26273	47680	43%	50%
	HIES						
2007-08	PSLM						
	HIES	Jul 07 -Jun 08	15512	6255	9257		
2008-09	PSLM	Aug 08 - Jun 09	75772	26975	48797	43%	50%
	HIES						
2009-10	PSLM						
	HIES						
2010-11	PSLM	Jul 10 - Jun 11	77488	27360	50128	50%	76%
	HIES	Jul 10 - Jun 11	16341	6589	9752		
2011-12	PSLM						
	HIES	Sep 11 - Jun 12	15807	6743	9064		
2012-13	PSLM	Oct 12 - Jun 13	75516	26598	48918	44%	54%
	HIES						
2013-14	PSLM						
	HIES	Aug 13 - Jun 14	17985	6234	11751		
2014-15	PSLM	Oct 14 - Jun 15	78635	13965	64670	63%	75%
	HIES						

Notes: PSLM, Pakistan Social and Living standard Measurement survey; HIES, Household Income Expenditure Survey. R sq. is of the Beta model of Small Area Estimation (SAE) techniques

4.3.1 Conventional Poverty Indices

The conventional poverty indices calculated are the Headcount, Poverty Gap, and Squared Poverty Gap, all based on consumption rather than income as the welfare proxy.[6] Given the aim to calculate these indices at district-level while existing analyses from the HIES data give conventional poverty measures only at the national and the provincial level, the survey-to-survey SAE imputation method is used. Specifically, the consumption of households in the HIES sample is modelled using a set of 'X' characteristics that have the same distribution in

[6] For debate in the literate about these alternative welfare indicators see Ravallion (2015)

the PSLM, and the coefficients from these models are then applied to the PSLM data to predict consumption for households in the PSLM sample. Dang et al. (2019) use data for Vietnam to show the robustness of this type of survey-to-survey imputation.

A key requirement of this method, explained in the work of Tarozzi (2007) is that the set of 'X' characteristics is comparable across both surveys, in terms of having the same definitions and the same distributions (given they come from the same population). In the case of Pakistan, a key feature that helps with the success of the imputation method is that the HIES and PSLM are conducted at almost the same time, with fieldwork for each survey typically only a few months apart. Therefore I have used HIES data from 2004-05, 2005-06, 2007-08, 2010-11, 2011-12, and 2013-14 to impute consumption for households in the PSLM that were surveyed in 2004-05, 2006-07, 2008-09, 2010-11, 2012-13, 2014-15 respectively. The details on the survey period, the sample size, and the predictive accuracy of the imputation models are reported in Table 1. The imputation models explain up to three quarters of the variation in HIES household consumption, and so should be a good basis for predicting the consumption of households in the PSLM, and then calculating poverty statistics from these predicted data.

The rationale behind the selection of combinations of HIES and PSLM surveys to impute consumption is based on backward looking model. The consumption habits or patterns observed in previous months are used to impute consumption of the future months. This assumes the continuation of previous consumption patterns instead of using information of future consumption patterns and impute consumption for the previous periods. Hence, the logical direction is to use consumption patterns of previous months and impute future consumption patterns. It is sensible to use one's todays' consumption pattern to predict future's consumption instead of using future consumption patterns to predict historical trends if we have access to the information from previous periods. As future consumption patterns could drastically alter due changing future consumption preferences or patterns. However, to test the sensitivity of poverty estimates, HIES 2007-08 is used to impute consumption into PSLM 2006-07. The poverty estimates calculated from this combination holds the trends I have observed using backward linking of the surveys. The conventional poverty estimates for national and provincial level for this robust check are reported in Appendix G.

The PSLM and HIES variables examined for overlapping distributions are broadly classified into following categories; household size, gender and years of schooling of the household head, the number of people in different age brackets, employment status of family members, the number of females in the household, ownership of various durable assets, access to services, dwelling status and facilities, and regional dummies.[7] For the selected variables, the SAE technique of Elbers et al. (2003) is followed, which is implemented through STATA commands from Nguyen et al. (2018). The dependent variable Y is used in logarithmic form which accounts for the skewed distribution of the consumption data (Haslett et al., 2010).

The SAE model consists of these two equations

$$Ln\,(Y) = \alpha + \beta(X) + \mu \quad \ldots\ldots 1$$

where Y represents consumption[8] per adult equivalent,[9] X is the set of characteristics, and the error term μ has two components (a cluster specific component and an idiosyncratic component).

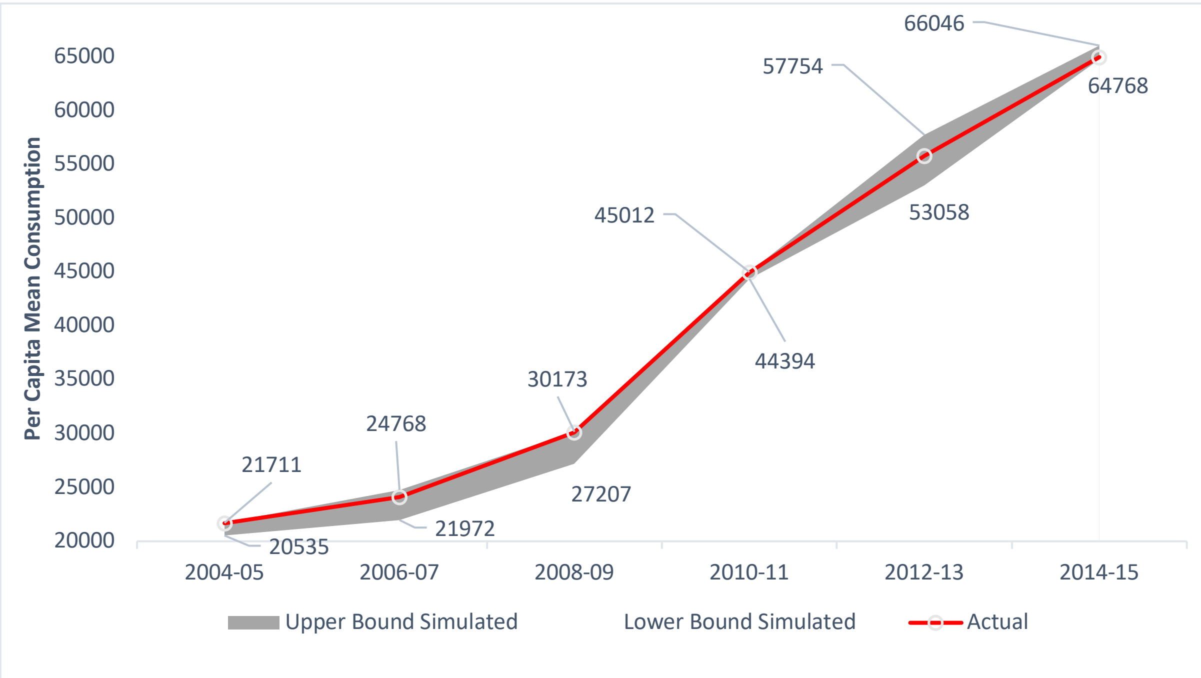
$$\mu_{ch} = \eta_c + e_{ch} \quad \ldots\ldots 2$$

[7] The variables included for each survey year and sector (urban and rural) are available from the author. This satisfies the second prerequisite of same distribution for survey-to-survey imputation.
[8] Consumption of goods purchased from market, received as gifts and home produced instead of just focusing on expenditure. (see Deaton, A. & Grosh, M. (2000). Consumption, in Designing Household Survey Questionnaires for Developing Countries: Lessons from 15 Years of the Living Standards Measurement Study. Eds Grosh, M. and Glewwe, P. The World Bank.: Washington, D. C.).
[9] The numbers of individuals with age below 18 years have given 0.8 weightage in calculation of household size whereas number of individuals with age above 18 years have given full weightage of 1

The subscript c stands for clusters in the survey and h stands for households. The households in the cluster are not independent of each other and the SAE method takes account of this. In both surveys the clusters are the primary sampling units.

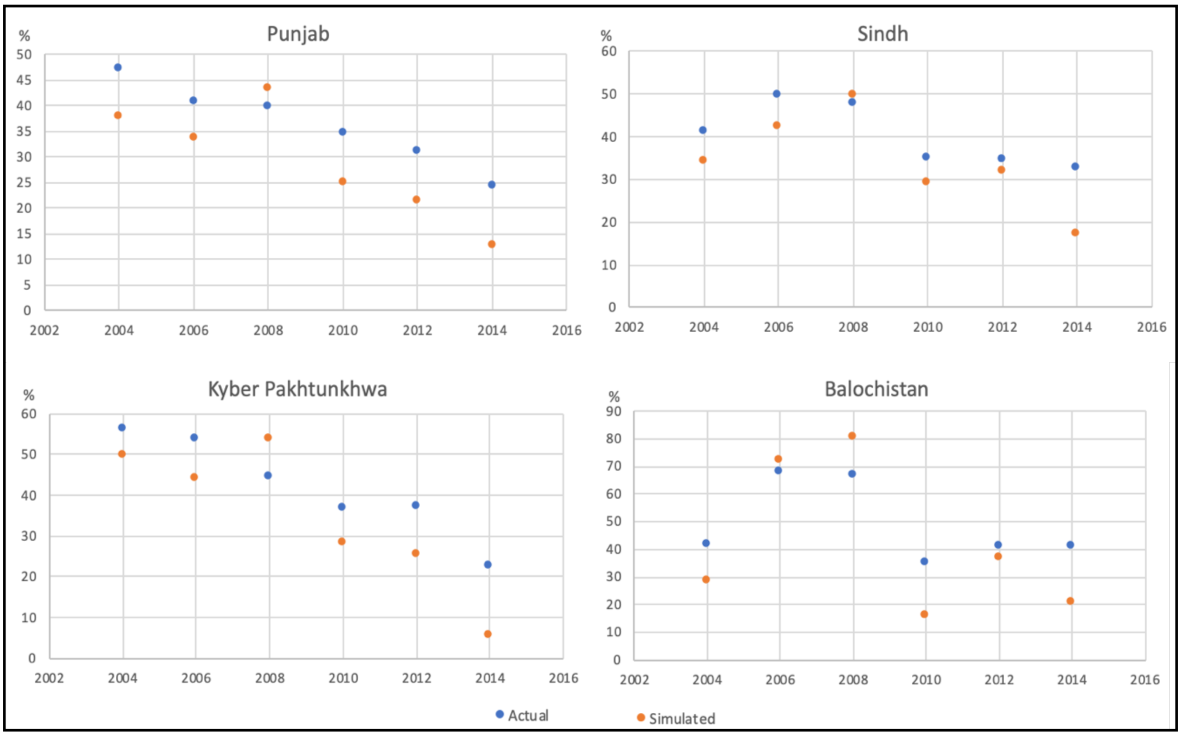
The first stage model (equation 1) of the SAE is estimated both at the national level and the sectoral (rural and urban) level, separately for each of the six years. In the second stage after imputing parameters into the PSLM sample, predicted consumption is used to calculate poverty estimates at the district-level. The predicted consumption data used in the calculation are from the model estimated for the regional domains, as Demombynes and Ozler (2005) note that estimating models for urban and rural domains separately provides better predictions. Also, in our case, as shown in Figure 1 the actual average per capita consumption from HIES falls within the 95% confidence intervals of the predicted average per capita consumption from PSLM. As Tarozzi (2007) suggested as a robustness check for the simulations, the distributions of consumption from HIES and the imputed consumption should be same.

Figure 1: 95% Confidence interval for simulated mean per capita consumption and actual mean per capita consumption



As another cross-check, Figure 2 shows the Headcount Index calculated from actual consumption data from HIES and from simulated consumption data from PSLM for provinces. Fairly similar changes over time are observed with only slight variations (see Figure 2).

Figure 2: Poverty headcount from HIES (actual) and PSLM (simulated) data for Provinces



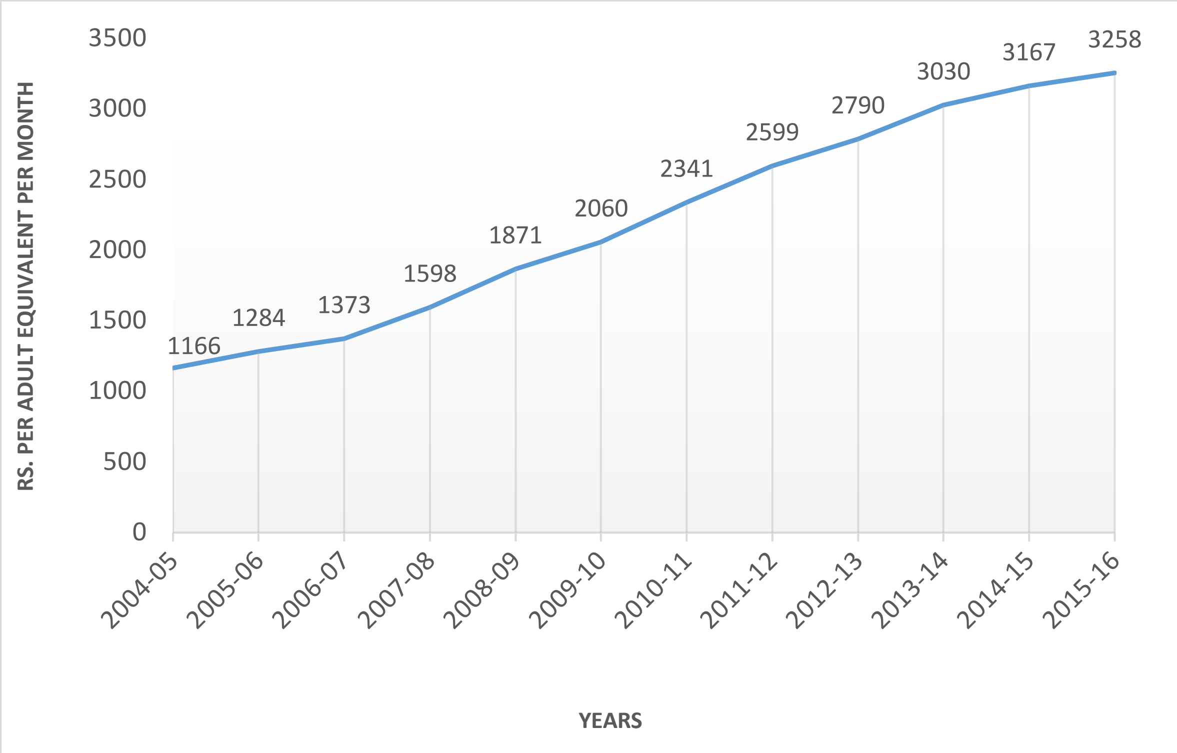
The adjusted R^2 from the SAE models range from 45 percent to 75 percent.[10] The key summary statistics from the SAE models are in Appendix B. The ratio of the cluster effect to the total mean squared error, which is an important diagnostic for the success at reducing the cluster correlated effect that will impair precision of the predictions, ranges from 0.1 to 0.4.

The ultimate goal of the SAE models is to enable trend analysis for conventional and non-conventional poverty measures, at district-level. The analysis uses the national poverty line

[10] The detailed SAE output for all the six years at urban and rural domains is available from author

calculated by the Government of Pakistan, and adjusted by the CPI for the years that the poverty line was not given.[11] The calculation of the national poverty line is based on Cost of Basic Needs (CBN) method. The poverty lines used for the study are at Figure 3.

Figure 3: Poverty Line (Rs. Per adult equivalent per month)



In terms of conventional poverty indices, three are calculated for the analysis:

The Head count index HH = $\left({}^{q}/_{n}\right) \times 100$

where q is the number of poor people living below the poverty line and n is the size of population. The headcount index is the proportion of persons living below the poverty line. It is easy to interpret but does not satisfy transfer and redistribution axioms (explained earlier).

[11] Planning Commission Pakistan (2018), National Poverty Report Pakistan 2015-16

$$\text{The Poverty Gap index, PG} = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z - Y_i}{Z}\right)\right)}{n} \times 100$$

where Z is the Poverty Line and Y_i is individuals i's consumption. This index is the average proportional shortfall from the poverty line as a ratio of poverty line (if consumption is greater than poverty line then it is set equal to zero) averaged over the population. While it measures the average depth of poverty it does not satisfy the transfer axiom and redistribution axiom.

$$\text{The Squared Poverty Gap index, SPG} = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z - Y_i}{Z}\right)^2\right)}{n} \times 100$$

The squared poverty gap is a distributionally sensitive measure.

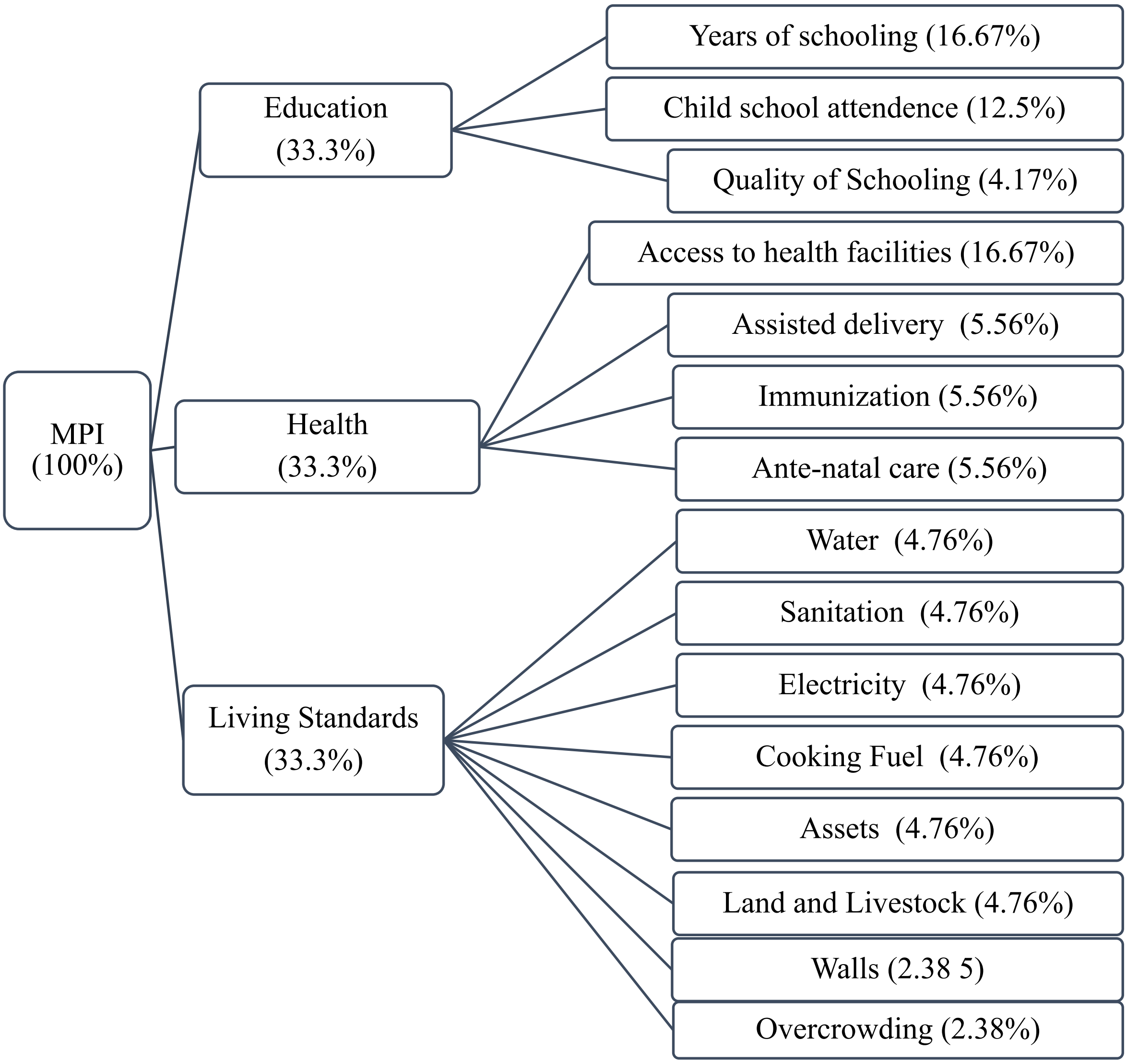
4.3.2 Non-Conventional Poverty Indices

The non-conventional poverty indices used are, Alkire and Foster (2011) Multidimensional Poverty Index, MPI and Datt (2019) Multidimensional Distribution-sensitive Poverty Index, MDPI. Also the headcounts (number of poor people) using both MPI and MDPI are calculated, MPI-HH and MDPI-HH respectively. For these measures, the list of 15 indicators come under three broad dimensions: Education, Health and Living Standards are considered. Under the dimension of education it relies on years of schooling, child school attendance, and educational quality. Under the dimension of health it relies on access to health Facilities/clinics/basic health units (bhu), immunization, ante-natal care, and assisted delivery. Under the dimension of living standards the sub-indicators used are water, sanitation, walls, overcrowding, electricity, cooking fuel, assets, and a land/livestock.

Both the multidimensional poverty indices are weighted averages of their indicators. Like the poverty line, the weights used for aggregation are the ones incorporated by Government of

Pakistan in their official report,[12] so that a legit comparison can be carried out. It has assigned 1/3 of the MPI's total weight to each of the three core dimensions: education, health and living standards. The nested weighted structure is used for all the sub-indicators (see Figure 4).

Figure 4: Nested weighted structure for multidimensional indicators



[12] UNDP Pakistan. (2016). "Multidimensional poverty in Pakistan" in collaboration with Ministry of Planning, Development and Reforms, Pakistan.

4.3.2.1 Multidimensional Poverty Index (MPI)

$$\text{MPI} = \text{M}\ (\alpha,\ \text{k};\ \text{y}) = \frac{1}{n}\sum_{i=1}^{n} \left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right) I_{i}^{k} \times 100$$

For *n* individuals and *d* total dimensions, $g_{ij}^{\alpha}=\left(1-y_{ij}/z_j\right)^{\alpha} I_{ij}$ for $\alpha \geq 0$ is defined as the indicator for deprivation in dimension *j* for an individual *i* where z_j is the cut-off point for the dimension *j*. $I_{i}^{k} = I(C_i \geq k)$ is defined as the poverty indicator in which *k* is the cut-off point for the number of dimensions in which an individual has to be deprived to be counted as poor and C_i is the sum of dimensions in which an individual *i* is deprived. $C_i = \sum_{j=1}^{d} I_{ij}$

The Alkire-Foster (AF) methodology uses dual cut off points. The first cut-off within a dimension is to identify deprivation in the dimension. If an individual is below the certain cut-off point in an indicator she/he is referred to as deprived in that dimension. The second cut-off identifies the individual as poor. In the present study if the aggregate score of an individual is above 33 percent they are termed as poor, that is the second cut-off point.[13] The first cut-off point for all the indicators are as follows:[14]

For the dimension of education: Years of schooling; deprived if no man or no woman in the household above 10 years of age has completed five years of schooling. Child school attendance; deprived if any school-aged child is not attending school (between 6 and 11 years of age). School quality; deprived if any child is not going to school because of quality issues

[13] The MPI poverty estimates for zero percent second cut-off point are reported in the appendices but not discussed in the text because there is 0.997 correlation between MPI 0 cut-off and MPI 33% cut-off point.

[14] These deprivation cut-offs for the dimensions are acknowledged by Govt. of Pakistan in the report, UNDP Pakistan. (2016). "Multidimensional poverty in Pakistan" in collaboration with Ministry of Planning, Development and Reforms, Pakistan

(not enough teachers, schools are far away, too costly, no male/female teacher, substandard schools), or is attending school but remains dissatisfied with service.

In the dimension of health: Access to health facilities like Basic Health Units (BHU); deprived if health facilities are not used at all, or are only used once in a while, because of access constraints (too far away, too costly, unsuitable, lack of tools or staff, not enough facilities). Immunization; deprived if any child under the age of 5 is not fully immunized according to the vaccination schedule (households with no children under 5 are considered non-deprived). Ante-natal care; deprived if any woman in the household who has given birth in the last three years did not receive ante-natal check-ups (household with no woman who has given birth are considered non-deprived). Assisted delivery; deprived if any woman in the household has given birth in the last three years attended by untrained personnel (family member, friend, traditional birth attendant, etc) or in an inappropriate facility (home, other) (households with no woman who has given birth are considered non deprived).

In the dimension of living standards: Water; deprived if the household has no access to an improved source of water according to Millennium Development Goals (MDG) standards, considering distance (less than a 30 min return trip) and type (tap water, hand pump, motor pump, protected well, mineral water). Sanitation; deprived if the household has no access to adequate sanitation according to MDG standards (flush system, privy seat). Walls; deprived if the household has unimproved walls (mud, uncooked/ mud bricks, wood / bamboo, other). Overcrowding; deprived if the household is overcrowded (four or more people per room). Electricity; deprived if the household has no access to electricity. Cooking fuel; deprived if the household uses solid cooking fuels for cooking (wood, dung cakes, crop residue, coal / charcoal, other). Assets; deprived if the household does not have more than two small assets (radio, tv, iron, fan, sewing machine, video cassette player, chair, watch, air cooler, bicycle)

OR no large asset (refrigerator, air conditioner, tractor, computer, motor cycle), AND has no car. Land and livestock (only for rural areas); deprived if the household is deprived in land by having less than 2.25 acres of non-irrigated land or less than 1.125 acres of irrigated land and deprived in livestock by having less than two cattle, fewer than three sheep / goats, fewer than five chickens and no animal for transportation (urban households are considered non-deprived). Also, the sensitivity analysis is done to check if the dimensions are correlated. If the dimensions are correlated one of them should be used in construction of MPI. However, in this study the correlation between the dimensions lie below 40 percent (Appendix I). Hence, no dimensions are excluded from the construction of multidimensional poverty measures. Further, the MPI in this study follows the construction of the official MPI for Pakistan, so analyses with different weights and allowing for different correlation patterns is not needed in this case.

4.3.2.2 Multidimensional Poverty Headcount Index (MPI-HH)

$$\text{MPI-HH} = \left[\frac{1}{n}\sum_{i=1}^{n} I_i^k \right] \times 100$$

Where n is the number of individuals and $I_i^k = I(C_i \geq k)$ is defined as the poverty indicator. k is the cut-off point for the number of dimensions in which an individual has to be deprived to be counted as poor. $I_i^k = 1$ if $C_i \geq k$ or else $I_i^k = 0$

4.3.2.3 Multidimensional Distribution-Sensitive Poverty Index (MDPI)

$$\text{MDPI} = \text{M}\ (\alpha,\ \beta;\ y) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right)^{\beta} \times 100 \qquad \text{for } \alpha \geq 0 \text{ and } \beta \geq 1$$

For values of $\beta > 1$, the measure $M(\alpha, \beta; y)$ satisfies a cross-dimensional convexity axiom. The value of β can be interpreted as parameterizing the relative weight accorded to the multiplicity of deprivations (i.e., to the joint density of deprivations relative to the marginal distributions of single deprivations). Where;

$$g_{ij}^{\alpha} = (1 - \frac{y_{ij}}{z_j})^{\alpha} I_{ij} \quad for\ \alpha\ \geq 0$$

$I_{ij} = I(y_{ij} < Z_j)$ 0 – 1 deprivation indicator function.

and y_{ij} is the achievement of individual *i* in dimension *j* and z_j is the deprivation *j* cut-off point. I_{ij} is zero when y_{ij}>z_j and 1 when $y_{ij} \leq z_j$. Datt (2019) used union approach for poverty estimates so it does not require second cut-off point. The first cut-offs used for the indicators are the same as of the MPI discussed above.

4.3.2.4 Multidimensional Distribution-Sensitive Poverty Headcount Index (MDPI-HH)

$$\text{MDPI} - \text{HH} = \left[\frac{1}{n}\sum_{i=1}^{n} (I_i)\right] \times 100$$

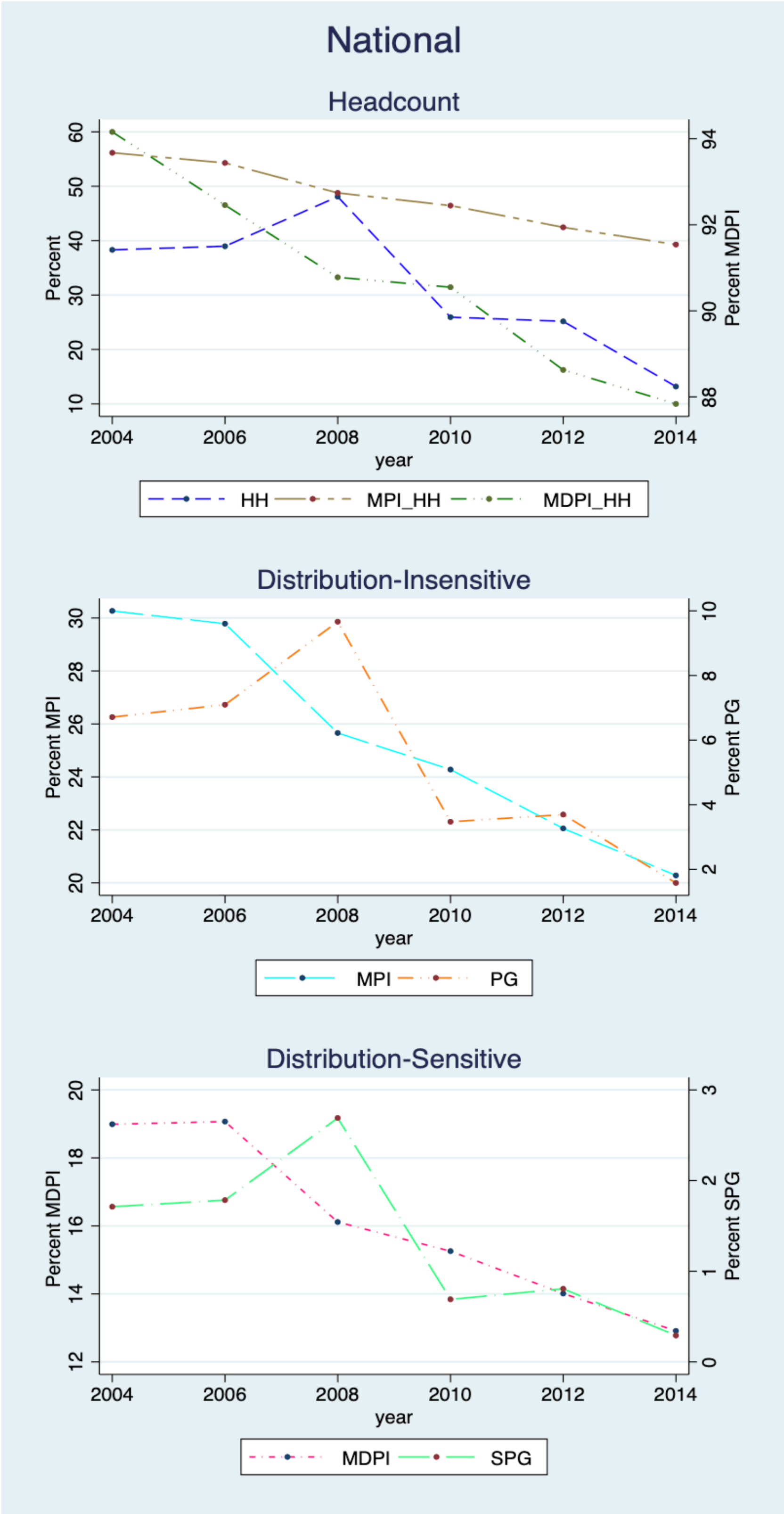
Where *n* is the number of individuals. $I_i = I(\sum_{j=1}^{d} I_{ij} > 0)$ is 0 – 1 poverty indicator function. I_i = 0 when $\sum_{j=1}^{d} I_{ij} = 0$ and I_i = 1 when $\sum_{j=1}^{d} I_{ij} > 0$. $I_{ij}$is zero when y_{ij}>z_j and is 1 when $y_{ij} \leq z_j$. y_{ij} is the achievement of individual *i* in dimension *j* and z_j is the deprivation *j* cut-off point.

4.4 Poverty Trends

Using the seven poverty indicators described above, the poverty trends for Pakistan using conventional and non-conventional measures while also allowing for the distribution-sensitivity is discussed ahead. At the National level (see Figure 5), from 2004 to 2014, there seems to be a fairly smooth decreasing trend for the non-conventional poverty indices (MPI and MDPI) whereas the conventional poverty indices (PG, SPG, HH) showed fluctuations with a rising poverty rate up until 2008 and a sharp declining trend thereafter.

The conventional headcount (HH) shows less poverty than the non-conventional headcount Index (MPI_HH), despite more volatility in the HH index. Thus, some people who are not poor in terms of money but are poor in multidimensional terms, deprived in usage/access to services and facilities. This may show trade-offs between consumption and other dimensions of wellbeing. If individuals are investing in buying assets for necessity or comfort they are cutting down on their consumption given their limited resources. A second feature from Figure 5 is that the non-conventional headcount indices (MPI-HH and MDPI-HH) show a more smoothly declining trend over all six survey years while there is a rise in the conventional headcount poverty index up until 2008 and then a sharp decline thereafter. So, the two types of head count indices depict different trends. Also, the dimensions of MPI are showing an overall declining trend over time (Appendix H). The highest deprivation remained for the access to education, access to health facilities and ownership of basic durables (assets).

Figure 5: Poverty trends at national level



Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

For Pakistan, the fluctuations in conventional money-metric poverty measures, especially the peak in 2008, is due to the higher food prices in 2008 which reduces the real value of consumption. World prices for some key staple foods tripled in 2007/08 which especially affected poverty Asia (Gibson and Kim, 2013). Likewise, Haq et al. (2008) show that Pakistan experienced higher poverty due to the effects of domestic food price inflation. However, this short-term shock is not translated into the declining trend of non-conventional poverty measures (MPI and MDPI). This declining trend is resulting from increased access to services as a result of long-term infrastructure development occurring during that time period. Thus, one contrast can be observed between conventional and multidimensional poverty trends, the money-metric poverty indicators (consumption/income) fluctuate more in the short-term due to price and income shocks while the dimensions (education, health, and living conditions) considered under non-conventional measures pick up on long-term improvements in infrastructure developments and access to services.

In part, because of the different time horizons that conventional and non-conventional poverty measures respond to, I generally see that for given spells between surveys the two types of indicator are not moving in the same direction. Details on these differences by spell in these poverty estimates can be seen in Appendix C for all the districts, and in Appendix D for the provincial and national level.

For many of the inter-survey spells these measures move in the opposite direction whether the distribution-insensitive class of poverty measures (PG and MPI) or the distribution-sensitive class (SPG and MDPI) is considered. Thus, at the national level, if I consider convexity in dimensions and severity in money deprivation, that is, if I put more weight on individuals farthest from the poverty line and those deprived in more dimensions, then the trend in the conventional poverty measure (SPG) is opposite to the trend in the non-conventional poverty measure (MDPI), for two spells. But if I do not give more weight to individuals who are farthest from the poverty line and those who are deprived in more dimensions, the trend in the conventional poverty measure (PG in this case) is opposite to the trend in the corresponding non-conventional poverty measures (MPI) for the majority of spells (at least 3 out of 5) at the national level (see Table 2).

Table 2: Number of spells (out of 5) for which poverty measures are moving in the opposite direction at the national level

DOMAIN	PG & SPG	PG & MPI	SPG & MDPI	MPI & MDPI
NATIONAL	0	3	2	1

Notes: PG, Poverty Gap Index; SPG, Squared Gap Index; MPI, Multidimensional Poverty Index; MDPI, Multidimensional Distribution-sensitive Poverty Index

If I just consider conventional poverty indices (HH, PG, SPG), the trends are exactly the same even if I give more weight to individuals farthest from the poverty line (that is, allowing for distributional sensitivity). In contrast, if I give more weight to the individuals who are deprived in more dimensions, then with the non-conventional poverty measures (MPI and MDPI) it will show opposite trends for one of the five spells, at the national level.

A corresponding analysis of whether trends diverge under conventional versus under the non-conventional poverty measures, but this time at the provincial level is reported in Table 3. It is distributionally sensitive measures that show diverging trends.

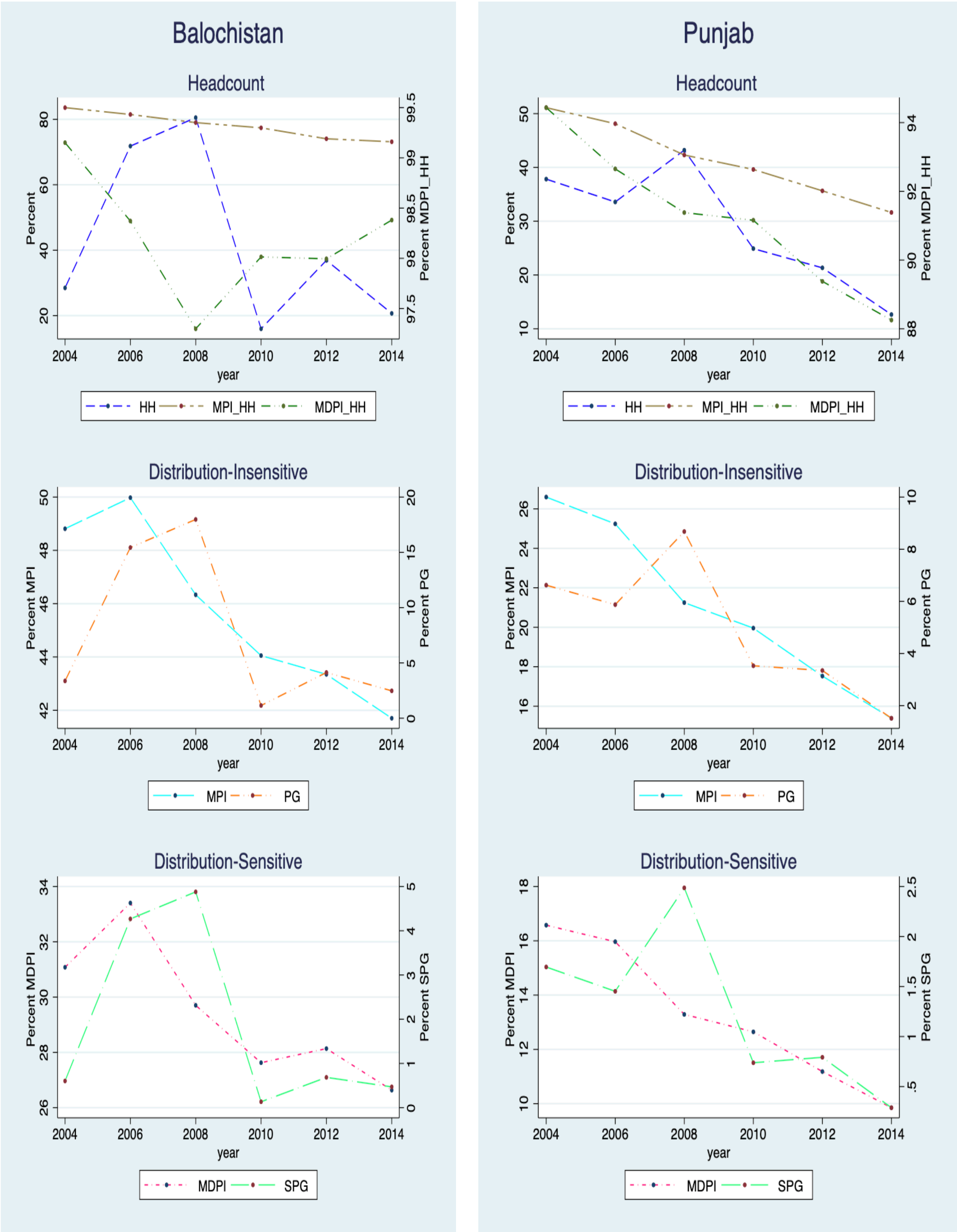
Table 3: Number of spells (out of 5) for which poverty measures are moving in opposite direction at provincial level

DOMAIN	PG & SPG	PG & MPI	SPG & MDPI	MPI & MDPI
KPK	0	1	1	0
PUNJAB	1	1	2	0
BALOCHISTAN	0	2	1	1
SINDH	0	2	2	0

Notes: PG, Poverty Gap Index; SPG, Squared Gap Index; MPI, Multidimensional Poverty Index; MDPI, Multidimensional Distribution-sensitive Poverty Index

The trends in poverty for Punjab, the most developed province (Pasha, 2015), and Balochistan, which is perhaps the least developed (World Bank, 2008), are shown in Figure 6. In Punjab, the distribution-sensitive conventional measure (SPG) and the non-conventional measure (MDPI) show opposite trends in two spells. For the distribution-insensitive class (PG and MPI), just one spell showed opposite movement. Thus, if more weight goes on to the individuals farthest from the poverty line or having more sets of dimensional deprivation, the conventional and non-conventional poverty measures are more likely to shows opposite movement in trends. Also, the multidimensional measures showed continuously declining trend in the headcount but the money-metric measures showed volatility over time. Thus, a more developed province shows that poverty trends are sensitive to using measures that respect the axiom of distribution-sensitivity (sensitive to how far people are from poverty line/cut-off).

Figure 6: Poverty trends at provincial level (Punjab and Balochistan)

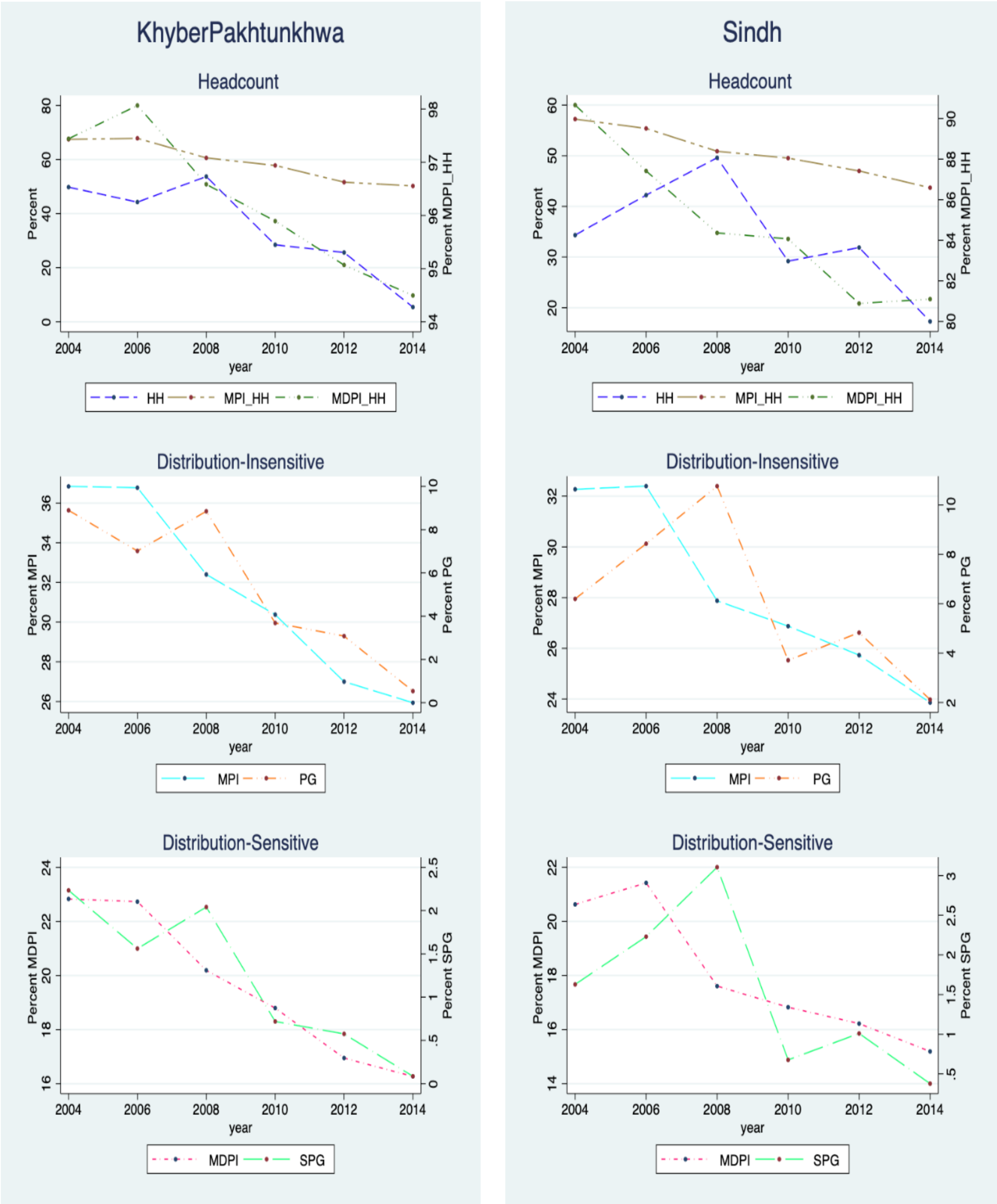


Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Inde

For Balochistan, the choice of poverty measure (conventional or non-conventional) showed substantial difference in trends (PG and MPI) if I do not consider giving more weight to people living far from poverty line/cut-off. MPI showed declining trend after 2006 whereas volatility is observed in money-metric poverty index (PG). People might be progressing in terms of accessing services/facilities but they are experiencing volatility in their monetary status. But if I consider distribution-sensitivity in poverty measures (SPG and MDPI) the trend is the same except for one spell. The fact that if I give more weight to people who are far from the poverty cut-off, the multidimensional measures showed variability in their trend highlighting the increase in severity of dimensional deprivation. If I compare MPI and MDPI I see decline in MPI but volatility in MDPI. This is because of the fact that distribution-sensitive dimensional poverty measure (MDPI) picks up on the non-uniformity in access to services/facilities. Giving more weight to people who are farthest from poverty cut-off has induced a slight increase in trend post 2006 in MDPI. In the case of least developed province the poverty trends are sensitive to the selection of poverty measures (conventional or non-conventional) if distribution-insensitivity is considered.

For the province of Kyber Pakhtunkhwa (the third most populous), apart from one spell the movements in the conventional and the non-conventional poverty measures are the same irrespective of whether the poverty measures are distribution-sensitive (see Figure 7). Both types of measure show declining trends except for 2008 where money-metric poverty rose. Finally, for Sindh (the 2nd most populous province), both class of measures show opposite movements in two of the spells irrespective of distribution-sensitivity. In all the cases, conventional poverty measures have shown the most volatility while the non-conventional poverty measures show a smoother decreasing trend overall. In some cases the dimensional poverty measure has picked up on the severity in dimensional deprivation resulting into volatility in the trend.

Figure 7: Poverty trends at provincial level (Sindh and Khyber Pakhtunkhwa)



Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

In sum, at the National and Provincial level, sensitivity of poverty trends to the choice of poverty measures (convention and non-conventional) is evident. Researching the poverty trends at the more disaggregated level, district, shows the same results. About 70 percent of the districts in all four provinces have showed opposite movement in trends for at least 2 spells out of 5. In total around 40 percent of districts have shown opposite movement in poverty trends for at least 3 spells using conventional and non-conventional poverty measures (see Table 4).

Table 4: Percentage of districts showing opposite movement in poverty trends using different poverty measures for at least 3 spells and at least 2 spells* (out of 5)

DOMAIN	PG & SPG	PG & MPI	SPG & MDPI	MPI & MDPI
BALOCHISTAN	0	38 (61)	35 (70)	0 (4)
KPK	0	48 (83)	35 (65)	0 (0)
PUNJAB	0	40 (71)	40 (83)	0 (8)
SINDH	0	62 (75)	56 (81)	0 (0)
NATIONAL	0	45 (73)	39 (75)	0 (4)

Notes: * percentage of districts with opposite moments for at least 2 spells out of 5 are shown in parenthesis (). PG, Poverty Gap Index; SPG, Squared Gap Index; MPI, Multidimensional Poverty Index; MDPI, Multidimensional Distribution-sensitive Poverty Index.

When results from the three spatial levels – national, provincial, and district – are put together, it is clear that the smooth reduction in poverty according to non-conventional multidimensional measures is not reflected in a corresponding pattern of poverty when measured with conventional money-metric indicators. This difference in the trends for these two types of measures suggests that improvements in access to services and facilities, which is picked up by the multidimensional measures, is not reflected in rising values of real consumption, at least in the short term. Likewise, if distribution-insensitive measures (PG and MPI) is considered, the opposite trend in poverty rates when using conventional versus non-conventional measures is found in over three-quarters (73%) of districts. The districts that show opposite trends in poverty changes when using conventional versus non-conventional measures are mapped in Appendix E (see Figure E1 and E2). The districts that show divergent trends for a majority of inter-survey spells can be found in all parts of the country, they are not specific to a province.

The year-by-year spatial patterns in each of the seven poverty measures that I consider are mapped in Appendix F. While there is heterogeneity within provinces, with some districts having higher poverty rates than others, a general spatial pattern is that poverty rates are highest in the south and west of Pakistan, which includes the provinces of Balochistan, parts of Sindh and south parts of Punjab. Despite the reduction in poverty rates between 2004 and 2014, these spatial patterns are still apparent, in both the conventional and the non-conventional poverty measures.

The results from the trend analysis and the fact that multidimensional measures show a smoother fall in national poverty rates raises the question of what inferences the Government of Pakistan should take from the evidence and use for policy making purposes. Government of Pakistan (GoP) has Public Sector Development Programme (PSDP) which is geared towards achieving socio-economic objectives of Government. In PSDP the financial allocation is made towards different development programmes. GoP can use multidimensional poverty indices to identify the areas that needs attention for infrastructure and services development. This way GoP can devise effective development interventions with long-term poverty eradicating effects. As conventional measures show fluctuations over the period of time, it may be more suitable for highlighting the vulnerability of the poor so, GoP may rely on money metric poverty measures to gauge the support needed by the poor when facing temporal fluctuations. Important thing to observe here is that the policy makers can use multidimensional poverty measures to study the impact of development programmes on poverty instead of using money metric poverty measures. Policy makers can utilise multidimensional poverty measures to research the sustainability aspect of interventions designed to help the poor. However, for dealing with short term shocks, because of the vulnerability of the poor, the GoP may depend on money metric poverty measures.

4.5 Conclusions

Policy analysts relies on poverty measures to identify the deprived individuals along with the impoverished areas/regions and to monitor temporal poverty trends. The interest in monitoring poverty trends in developing countries is growing after the Sustainable Development Goals are embedded in public policy at both national and regional level. Recently, there has been a surge in the use of non-conventional multidimensional measures of poverty that either replace or supplement the conventional money-metric measures. Along with this change, there has been a growing focus on distribution-sensitive classes of poverty measures that can provide richer information on disparities in living standards. These methodological changes are salient for Pakistan, which increasingly relies on multidimensional poverty measures coming from the biennial Pakistan Social and Living Standards Measurement surveys.

This study examines whether the same trends in poverty are apparent if an analysis uses either the conventional or the multidimensional approaches, while also considering distributionally sensitive versus insensitive poverty measures among them. The empirical part of the analysis relies on linking multi-topic surveys PSLM fielded every second year (from 2004 to 2014) to household expenditure surveys HIES fielded in alternating (or sometimes overlapping) years. With this linkage I am able to create a longitudinal database at the district, provincial and national level, that has poverty estimates from both the conventional and non-conventional approaches in six different years, giving five inter-survey spells that are the focus of many of the results.

The multidimensional measures show a smoother fall in national poverty rates while the conventional measures show rising poverty up until 2008 and then a sharper fall. Almost two-third of the districts show opposite trends in poverty for at least two of the five spells between the surveys when using the conventional approach rather than the multidimensional poverty measures, irrespective of whether distribution-sensitivity is considered or not. One reason for the different trends is that real consumption may fluctuate even if there is better access to services and facilities. The conventional poverty measures are receptive to the inflation shocks in the economy, such as the food price shocks in 2008, which multidimensional poverty measures are not.

In addition to the apparent difference in temporal poverty trends of conventional or non-conventional measures, the cross-sectional pattern of poverty is also affected. For example, many of the districts which are in the top-tier of income deprivation are not in the top-tier of multidimensional deprivation. The most developed province Punjab, where the poverty trends seem to go in the same direction for distribution-insensitive conventional and multidimensional poverty measures but the poverty estimates show discordant trends when distribution sensitive conventional and multidimensional poverty measures are used. In other words, if I consider convexity in deprivation then conventional and multidimensional measures of poverty are showing opposite progress for majority of inter-survey spells. Observing declining trends when poverty is calculated using access to services and facilities does not assure declining trend when poverty is calculated on the basis of consumption/income status. At least in short-term, the progress made under access to services and facilities is not translated into increased level of consumption/income.

Thus, apparent trends are sensitive to the poverty measurement approach used, so policy analysts should be cautious in the conclusions they draw from poverty estimates. If policy makers are relying on multidimensional poverty measures, to analyze poverty-stricken regions, in the case of Pakistan, they will see a reduction in number of people deprived of improved access to services. But if they rely on money-metric poverty measures they will see volatility in number of people impoverished in terms of consumption/income.

Given the differing poverty trends of conventional and non-conventional poverty measures, further research can be conducted on what factors determine these variations. Particularly because the conventional measures show more volatility. Understanding the driving factors behind these differences could help policy makers to be more receptive and cautious towards future shocks the economy may experience.

Given the sensitivity of poverty trends to dimensionality and distribution-sensitivity in poverty measures, it requires circumspection on the part of policy analyst in the conclusions drawn from poverty trends.

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Appendix A

Table A1: Availability of districts data and the old definition of districts

Districts	2014	2012	2010	2008	2006	2004
			Punjab			
Attock	√	√	√	√	√	√
Rawalpindi	√	√	√	√	√	√
Jehlum	√	√	√	√	√	√
Chakwal	√	√	√	√	√	√
Sargodha	√	√	√	√	√	√
Bhakhar	√	√	√	√	√	√
Khushab	√	√	√	√	√	√
Mianwali	√	√	√	√	√	√
Faisalabad	√	√	√	√	√	√
Jhang	√	√	√	√	√	√
T.T. Singh	√	√	√	√	√	√
Chiniot	Jhang	Jhang	Jhang			
Gujranwala	√	√	√	√	√	√
Gujrat	√	√	√	√	√	√
Sialkot	√	√	√	√	√	√
Hafizabad	√	√	√	√	√	√
Mandi Bahuddin	√	√	√	√	√	√
Narowal	√	√	√	√	√	√
Lahore	√	√	√	√	√	√
Kasur	√	√	√	√	√	√
Okara	√	√	√	√	√	√
Sheikhupura	√	√	√	√	√	√
Nankana Sahib	sheikhupura	sheikhupura	sheikhupura	sheikhupura		
Vehari	√	√	√	√	√	√
Sahiwal	√	√	√	√	√	√
Multan	√	√	√	√	√	√
Khanewal	√	√	√	√	√	√
Pakpatten	√	√	√	√	√	√
Lodhran	√	√	√	√	√	√
D. G. Khan	√	√	√	√	√	√
Rajanpur	√	√	√	√	√	√
Layyah	√	√	√	√	√	√
Muzaffar Garh	√	√	√	√	√	√
Bahawalpur	√	√	√	√	√	√
Bahawalnagar	√	√	√	√	√	√
Rahim Yar Khan	√	√	√	√	√	√
Islamabad	√	√	√	√	√	√
			SINDH			
Khairpur	√	√	√	√	√	√
Sukkur	√	√	√	√	√	√
Nawabshah	√	√	√	√	√	√
Nowshero Feroze	√	√	√	√	√	√
Ghotki	√	√	√	√	√	√
Jacobabad	√	√	√	√	√	√
Kashmore	jacobabad	jacobabad	jacobabad	jacobabad		

Shikarpur	√	√	√	√	√	√
Larkana	√	√	√	√	√	√
Shahdadkot	larkana	larkana	larkana	larkana		
Dadu	√	√	√	√	√	√
Jamshoro	Dadu	Dadu	Dadu	Dadu		
Hyderabad	√	√	√	√	√	√
Matiari	Hyderabad	Hyderabad	Hyderabad	Hyderabad		
Tando Allah Yar	Hyderabad	Hyderabad	Hyderabad	Hyderabad		
Tando Muhammad Khan	Hyderabad	Hyderabad	Hyderabad	Hyderabad		
Badin	√	√	√	√	√	√
Thatta	√	√	√	√	√	√
Sanghar	√	√	√	√	√	√
Mir Pur Khas	√	√	√	√	√	√
Umer Kot	Mir Pur Khas	Mir Pur Khas	Mir Pur Khas			
Tharparkar	√	√	√	√	√	√
Karachi West	Karachi	√	√	√	√	√
Karachi Malir	Karachi					
Karachi South	Karachi					
Karachi East	Karachi					
Karachi Central	Karachi					
Sujawal	Thatta					
KPK						
Swat	√	√	√	√	√	√
Upper Dir	Dir	Dir	Dir	Dir	Dir	Dir
Lower Dir	Dir	Dir	Dir	Dir	Dir	Dir
Chitral	√	√	√	√	√	√
Shangla	√	√	√	√	√	√
Malakand	√	√	√	√	√	√
Bonair	√	√	√	√	√	√
Peshawar	√	√	√	√	√	√
Charsada	√	√	√	√	√	√
Nowsehra	√	√	√	√	√	√
Kohat	√	√	√	√	√	√
Karak	√	√	√	√	√	√
Hangu	√	√	√	√	√	√
D. I. Khan	√	√	√	√	√	√
Tank	√	√	√	√	√	√
Manshera	√	√	√	√	√	√
Abbottabad	√	√	√	√	√	√
Batagram	√	√	√	√	√	√
Kohistan	√	√	√	√	√	√
Haripur	√	√	√	√	√	√
Bannu	√	√	√	√	√	√
Lakki Marwat	√	√	√	√	√	√
Mardan	√	√	√	√	√	√
Swabi	√	√	√	√	√	√
Tor Garh	Manshera	Manshera				
BALOCHISTAN						
Quetta	√	√	√	√	√	√
Pishine	√	√	√	√	√	√
Qilla Abdullah	√	√	√	√	√	√

Chaghai	√	√	√	√	√	√
Nushki	Chaghai	Chaghai	Chaghai	Chaghai		
Sibbi	√	√	√	√	√	√
Ziarat	√	√	√	√	√	√
Kohlu	√	√	√	√	√	X
Dera Bugti	√	√	√	√	√	X
Harnai	Sibbi	Sibbi	Sibbi			
Kalat	√	√	√	√	√	√
Mastung	√	√	√	√	√	√
Khuzdar	√	√	√	√	√	√
Awaran	√	√	√	√	√	√
Kharan	√	√	√	√	√	√
Washuk	Kharan	Kharan	Kharan	Kharan		
Lasbela	√	√	√	√	√	√
Ketch/Turbat	X	√	√	√	√	√
Gwader	√	√	√	√	√	√
Panjgoor	X	X	√	√	√	√
Zhob	√	√	√	√	√	√
Loralai	√	√	√	√	√	√
Barkhan	√	√	√	√	√	√
Musa Khel	√	√	√	√	√	√
Qilla Saifullah	√	√	√	√	√	√
Sherani	Zhob	Zhob	Zhob			
Nasirabad/ Tamboo	√	√	√	√	√	√
Jaffarabad	√	√	√	√	√	√
Jhal Magsi	√	√	√	√	√	√
Bolan/ Kachhi	√	√	√	√	√	√

Appendix B

Table B1: SAE Model Results

Statistics	2004		2006		2008		2010		2012		2014	
	Urban	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**
Error Decomposition	ELL	ELL	ELL	ELL	ELL	ELL	ELL	ELL	ELL	ELL	ELL	ELL
Beta Model Diagnostics												
Number of Observations	5783	8879	6135	9159	6250	9247	6585	9748	6743	9062	6234	11751
Adjusted R Squared	0.669	0.449	0.501	0.431	0.494	0.430	0.755	0.497	0.531	0.435	0.745	0.623
R Squared	0.674	0.454	0.504	0.433	0.499	0.434	0.757	0.500	0.535	0.437	0.748	0.625
Root MSE	0.368	0.349	0.486	0.351	0.465	0.346	0.298	0.304	0.442	0.337	0.294	0.279
F Stat	159.61	86.02	137.67	188.47	116.31	111.61	307.63	166.94	187.71	175.10	309.96	324.69
Alpha Model Diagnostics												
Number of Observations	5783	8879	6135	9159	6250	9247	6585	9748	6743	9062	6234	11751
Adjusted R Squared	0.014	0.034	0.024	0.030	0.027	0.039	0.026	0.018	0.023	0.020	0.029	0.026
R Squared	0.023	0.040	0.029	0.033	0.034	0.044	0.033	0.022	0.025	0.023	0.034	0.029
Root MSE	2.327	2.240	2.300	2.280	2.310	2.248	2.237	2.257	2.302	2.284	2.264	2.241
F Stat	2.635	7.449	6.903	9.637	4.518	8.472	4.790	5.193	9.773	7.464	7.731	11.520
Model Parameters												
Sigma ETA Sq.	0.027	0.029	0.090	0.019	0.085	0.020	0.016	0.015	0.070	0.023	0.010	0.012
Ratio of Sigma ETA sq over MSE	0.202	0.238	0.377	0.157	0.394	0.169	0.184	0.164	0.357	0.200	0.121	0.161
Variance of Epsilon	0.108	0.093	0.147	0.104	0.131	0.100	0.072	0.077	0.126	0.091	0.076	0.065
Sampling Variance of Sigma eta sq	9.2×10^{-6}	4.4×10^{-6}	3.9×10^{-5}	2.4×10^{-6}	3.5×10^{-5}	2.5×10^{-6}	2.0×10^{-6}	1.3×10^{-6}	2.2×10^{-5}	2.9×10^{-6}	1.2×10^{-6}	7.6×10^{-7}

Appendix C

Table C1: Poverty Estimates at District-level[15]

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
				PUNJAB					
ISLAMABAD	2004	14.27	69.07	13.73	1.87	6.34	14.26	0.36	4.56
ISLAMABAD	2006	3.58	52.08	6.66	0.39	2.81	9.11	0.07	2.47
ISLAMABAD	2008	14.30	60.18	8.71	2.22	3.81	11.91	0.59	3.34
ISLAMABAD	2010	2.30	69.54	10.11	0.41	4.52	13.69	0.12	4.00
ISLAMABAD	2012	2.35	51.50	6.73	0.22	2.91	9.09	0.03	2.49
ISLAMABAD	2014	1.46	60.93	3.19	0.11	1.40	7.87	0.01	1.75
ATTOK	2004	31.56	95.05	43.37	5.22	19.90	30.19	1.23	12.03
ATTOK	2006	21.60	93.66	31.24	2.64	13.99	25.27	0.47	9.05
ATTOK	2008	31.84	92.28	31.94	4.56	14.10	25.33	1.00	9.02
ATTOK	2010	16.65	92.99	29.76	2.19	13.45	24.74	0.49	8.92
ATTOK	2012	10.94	89.45	18.89	1.88	7.91	18.91	0.70	5.74
ATTOK	2014	5.18	85.78	9.73	0.47	4.05	15.19	0.07	3.99
RAWALPINDI	2004	20.05	83.35	26.33	2.66	11.93	21.52	0.55	7.74
RAWALPINDI	2006	9.05	73.72	18.10	0.98	8.12	17.29	0.18	5.80
RAWALPINDI	2008	16.23	72.74	10.89	2.17	4.59	13.46	0.44	3.71
RAWALPINDI	2010	7.74	76.59	13.40	0.95	5.86	14.88	0.20	4.39
RAWALPINDI	2012	4.08	69.05	7.60	0.68	3.25	12.09	0.22	3.17
RAWALPINDI	2014	3.19	71.63	7.75	0.58	3.29	11.36	0.13	2.94
JHELUM	2004	27.73	96.48	34.24	4.30	16.03	26.63	1.04	10.20
JHELUM	2006	12.44	88.54	24.04	1.57	11.90	21.43	0.29	8.35
JHELUM	2008	27.91	86.80	6.40	4.01	2.59	13.32	0.84	3.01
JHELUM	2010	7.82	91.06	14.13	0.72	6.18	17.56	0.10	5.07
JHELUM	2012	7.26	85.05	9.93	0.67	4.28	14.46	0.09	3.84
JHELUM	2014	1.23	81.93	8.22	0.07	3.30	12.99	0.00	3.11
CHAKWAL	2004	17.64	96.28	25.67	2.13	11.40	24.12	0.41	8.04
CHAKWAL	2006	17.36	92.70	32.20	2.36	14.59	24.66	0.46	9.12
CHAKWAL	2008	19.08	91.99	21.68	2.27	9.07	20.22	0.38	6.19
CHAKWAL	2010	8.64	92.21	19.75	0.85	8.35	20.92	0.16	6.37
CHAKWAL	2012	4.02	92.08	11.39	0.30	4.69	17.74	0.05	4.73
CHAKWAL	2014	1.57	88.64	13.00	0.18	5.66	16.60	0.03	4.66
SARGODHA	2004	40.04	97.12	55.47	7.43	27.80	36.21	1.99	16.77
SARGODHA	2006	24.73	96.34	54.19	3.99	27.50	36.65	0.91	17.03

[15] Notes : Blue highlighted: Districts showing apposite trends for distribution-sensitive conventional and non-conventional poverty measures for at least 2 or more spells out of 5.

Red Font: Districts showing apposite trends for distribution-insensitive conventional and non-conventional poverty measures for at least 2 or more spells out of 5.

HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI-33, Multidimensional Poverty Index with 33% cut-off; MPI-0, Multidimensional Poverty Index with 0 cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
SARGODHA	2008	40.10	94.88	50.98	6.72	24.64	33.69	1.71	14.61
SARGODHA	2010	23.90	94.32	47.77	3.12	23.27	31.82	0.62	13.84
SARGODHA	2012	14.16	93.18	36.91	1.70	17.25	27.94	0.30	10.92
SARGODHA	2014	8.07	88.24	35.78	1.08	16.76	25.63	0.21	10.12
BHAKKAR	2004	44.53	99.40	75.25	7.50	41.13	46.53	1.80	24.87
BHAKKAR	2006	50.56	100.00	73.89	7.51	39.35	45.48	1.65	23.75
BHAKKAR	2008	54.41	99.84	71.52	10.33	36.75	43.10	2.84	21.45
BHAKKAR	2010	42.46	99.71	66.83	5.96	36.55	43.82	1.24	22.76
BHAKKAR	2012	34.00	99.08	61.17	4.11	29.81	37.92	0.75	17.17
BHAKKAR	2014	13.04	98.64	50.26	1.59	25.12	35.09	0.29	15.57
KHUSHAB	2004	33.41	99.15	59.82	5.54	30.24	38.22	1.41	18.08
KHUSHAB	2006	29.12	98.40	50.01	4.44	24.34	34.64	0.96	14.92
KHUSHAB	2008	42.25	95.89	55.58	7.17	27.19	35.78	1.61	16.02
KHUSHAB	2010	16.39	96.35	47.65	1.72	22.25	31.90	0.28	13.13
KHUSHAB	2012	18.83	96.53	40.82	2.95	18.75	29.46	0.67	11.53
KHUSHAB	2014	7.13	93.70	40.06	0.79	20.05	30.57	0.14	13.04
MIANWALI	2004	28.84	98.66	65.89	3.99	33.64	40.61	0.75	19.72
MIANWALI	2006	30.90	98.48	60.52	3.95	31.36	39.12	0.79	19.11
MIANWALI	2008	46.65	98.26	54.37	7.94	28.38	37.58	1.88	17.85
MIANWALI	2010	28.89	98.14	50.67	3.44	24.95	34.42	0.60	15.24
MIANWALI	2012	22.63	95.72	45.04	3.97	23.82	33.21	1.04	15.83
MIANWALI	2014	9.55	96.41	47.28	1.09	24.15	33.65	0.19	15.27
FAISALABAD	2004	28.90	90.96	37.63	4.25	18.23	27.38	0.96	11.39
FAISALABAD	2006	22.50	92.32	32.83	2.95	15.87	25.42	0.61	10.12
FAISALABAD	2008	38.08	91.75	28.28	7.40	12.81	22.82	2.05	8.22
FAISALABAD	2010	13.56	90.15	23.56	1.58	11.16	20.53	0.30	7.42
FAISALABAD	2012	10.90	88.70	19.34	1.50	8.67	19.16	0.33	6.26
FAISALABAD	2014	6.73	90.39	19.80	0.73	8.85	19.61	0.12	6.35
JHANG	2004	44.33	99.09	72.54	7.90	38.91	44.77	1.96	23.50
JHANG	2006	48.06	98.53	64.85	8.71	34.15	40.72	2.11	20.52
JHANG	2008	47.93	98.18	60.63	8.74	30.39	37.96	2.28	17.80
JHANG	2010	32.68	95.12	49.58	4.70	23.48	31.84	0.98	13.59
JHANG	2012	32.08	94.81	45.67	4.82	21.90	31.36	1.06	13.33
JHANG	2014	15.00	94.90	42.43	1.72	20.17	29.91	0.34	12.31
TOBATEKSINGH	2004	42.00	97.60	58.67	6.98	30.73	38.93	1.62	19.03
TOBATEKSINGH	2006	23.85	98.96	47.81	3.39	23.44	34.07	0.70	14.67
TOBATEKSINGH	2008	36.50	97.63	40.16	6.34	18.94	30.64	1.63	12.06
TOBATEKSINGH	2010	14.37	93.02	26.09	1.85	12.01	23.45	0.37	8.32
TOBATEKSINGH	2012	18.24	94.35	33.01	2.14	15.01	26.28	0.40	9.65
TOBATEKSINGH	2014	7.82	95.01	24.31	0.90	10.93	22.22	0.17	7.48
GUJRANWALA	2004	31.88	94.16	34.12	4.75	15.96	26.66	1.00	10.17
GUJRANWALA	2006	15.68	89.51	29.55	2.02	13.33	23.41	0.39	8.48
GUJRANWALA	2008	28.96	84.39	19.44	4.54	8.46	19.45	1.10	6.17
GUJRANWALA	2010	10.43	84.20	18.93	1.10	8.44	19.54	0.20	6.33
GUJRANWALA	2012	7.24	82.90	17.56	0.85	7.71	17.96	0.17	5.72
GUJRANWALA	2014	7.64	80.54	13.43	0.80	6.26	16.09	0.16	5.06
GUJRAT	2004	26.10	91.79	30.42	4.03	14.37	25.15	0.91	9.54
GUJRAT	2006	17.70	89.75	22.63	2.25	9.87	20.26	0.46	6.60
GUJRAT	2008	26.63	92.47	20.46	4.30	8.88	22.46	1.02	7.04

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
GUJRAT	2010	11.94	91.08	21.69	1.27	9.83	22.50	0.22	7.49
GUJRAT	2012	9.85	83.73	18.50	1.27	7.95	18.99	0.27	5.91
GUJRAT	2014	3.00	84.07	18.58	0.36	7.90	19.30	0.06	5.99
SIALKOT	2004	27.23	95.63	35.39	3.80	15.87	28.10	0.84	10.31
SIALKOT	2006	25.93	98.85	43.11	3.47	20.70	32.68	0.71	13.43
SIALKOT	2008	43.74	91.13	25.73	7.49	11.31	23.36	1.91	7.96
SIALKOT	2010	11.67	93.53	28.16	1.15	12.80	25.34	0.18	8.90
SIALKOT	2012	10.90	92.48	24.16	0.94	10.92	23.79	0.13	8.04
SIALKOT	2014	4.07	86.53	14.41	0.38	6.06	16.68	0.05	4.82
HAFIZABAD	2004	35.35	99.23	58.33	5.25	30.17	38.11	1.09	18.36
HAFIZABAD	2006	36.49	96.45	47.61	5.95	22.08	31.27	1.31	12.80
HAFIZABAD	2008	41.11	95.03	35.94	7.06	16.63	27.94	1.78	10.69
HAFIZABAD	2010	25.21	91.32	38.48	3.03	18.24	27.46	0.57	11.07
HAFIZABAD	2012	19.50	94.03	32.60	1.83	14.45	25.51	0.28	9.11
HAFIZABAD	2014	9.21	88.64	32.30	0.91	15.31	25.64	0.15	9.89
MANDIBAHAUDIN	2004	27.43	98.54	52.77	3.84	26.15	35.83	0.83	15.96
MANDIBAHAUDIN	2006	28.97	96.72	39.54	4.17	18.86	29.69	0.90	11.91
MANDIBAHAUDIN	2008	40.25	94.51	36.52	6.18	16.76	28.15	1.52	10.70
MANDIBAHAUDIN	2010	10.50	93.82	40.05	1.02	18.16	28.87	0.14	11.08
MANDIBAHAUDIN	2012	10.58	91.61	27.88	1.10	12.35	25.17	0.19	8.63
MANDIBAHAUDIN	2014	8.03	93.78	32.25	1.32	14.99	26.66	0.31	9.92
NAROWAL	2004	28.99	99.43	51.03	3.93	24.31	34.57	0.87	14.58
NAROWAL	2006	44.31	99.50	62.10	6.34	29.98	38.91	1.26	17.43
NAROWAL	2008	49.90	99.31	50.09	8.41	23.31	35.28	1.97	14.42
NAROWAL	2010	26.14	98.65	40.98	2.97	18.41	31.09	0.48	11.78
NAROWAL	2012	24.06	99.78	46.44	2.73	21.03	33.32	0.49	13.00
NAROWAL	2014	9.56	96.73	27.07	0.91	11.87	25.12	0.13	8.44
LAHORE	2004	15.48	75.52	16.41	2.17	7.48	16.11	0.51	5.29
LAHORE	2006	10.24	73.39	13.95	1.43	6.28	14.72	0.31	4.65
LAHORE	2008	16.52	67.76	9.90	2.92	4.46	12.05	0.78	3.53
LAHORE	2010	9.24	68.85	12.14	1.22	5.38	12.83	0.24	3.92
LAHORE	2012	4.55	63.11	7.26	0.53	3.26	10.30	0.09	2.89
LAHORE	2014	4.12	67.43	4.99	0.29	1.92	8.03	0.04	1.78
KASUR	2004	42.65	97.83	50.55	7.03	24.34	33.01	1.76	14.37
KASUR	2006	37.09	97.90	53.88	5.83	26.92	35.69	1.29	16.22
KASUR	2008	50.96	97.18	45.76	10.19	20.76	30.56	2.73	12.09
KASUR	2010	25.83	96.89	39.00	2.80	18.34	28.77	0.47	11.40
KASUR	2012	19.91	95.86	36.66	2.81	16.68	27.18	0.60	10.33
KASUR	2014	12.14	94.13	21.31	1.22	9.32	21.13	0.18	6.84
OKARA	2004	38.37	99.73	67.02	6.31	34.79	41.49	1.56	20.66
OKARA	2006	44.98	98.13	64.07	8.51	35.05	42.16	2.13	22.05
OKARA	2008	48.90	95.00	51.59	10.02	25.52	34.32	2.79	15.42
OKARA	2010	31.78	96.40	53.52	4.42	26.11	34.45	0.88	15.39
OKARA	2012	21.37	94.84	46.67	2.75	22.03	31.13	0.58	12.95
OKARA	2014	14.08	91.07	39.63	1.45	18.68	27.83	0.27	11.25
SHEIKHUPURA	2004	37.63	94.57	39.71	6.33	19.08	29.17	1.63	12.04
SHEIKHUPURA	2006	30.01	95.42	47.02	4.38	23.18	32.22	0.95	14.12
SHEIKHUPURA	2008	41.77	92.52	32.70	7.81	15.23	25.62	2.14	9.74
SHEIKHUPURA	2010	21.82	91.49	32.38	2.37	15.46	25.56	0.42	9.98

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
SHEIKHUPURA	2012	15.19	87.09	25.72	2.15	11.95	22.01	0.44	8.04
SHEIKHUPURA	2014	9.19	89.42	22.26	0.80	9.83	20.66	0.12	6.84
VEHARI	2004	49.34	99.41	57.68	9.17	27.85	36.18	2.39	16.17
VEHARI	2006	48.50	98.66	56.80	9.33	27.92	36.12	2.45	16.38
VEHARI	2008	56.00	97.81	47.56	11.59	22.15	31.32	3.24	12.89
VEHARI	2010	33.95	98.08	46.10	4.61	21.70	31.69	0.92	12.98
VEHARI	2012	32.93	98.93	57.53	5.47	29.65	38.46	1.31	18.21
VEHARI	2014	17.71	95.92	42.07	1.98	20.15	30.33	0.35	12.64
SAHIWAL	2004	38.81	97.76	57.98	6.20	29.78	37.58	1.46	18.12
SAHIWAL	2006	35.45	97.90	55.03	5.92	28.63	36.89	1.42	17.74
SAHIWAL	2008	52.28	95.82	50.65	10.52	25.04	33.73	3.18	15.05
SAHIWAL	2010	25.95	94.42	42.30	3.29	20.63	29.82	0.59	12.58
SAHIWAL	2012	24.80	93.53	37.79	4.31	18.28	27.64	0.99	11.29
SAHIWAL	2014	13.80	89.98	31.76	1.65	14.38	23.32	0.34	8.70
MULTAN	2004	44.64	94.52	56.62	8.73	28.74	35.47	2.43	16.89
MULTAN	2006	36.46	91.75	53.43	6.56	28.54	35.00	1.64	17.57
MULTAN	2008	44.70	91.91	51.05	9.38	25.97	33.64	2.71	15.64
MULTAN	2010	29.78	90.74	45.66	4.02	23.41	31.05	0.82	14.40
MULTAN	2012	23.47	89.33	43.82	3.67	22.03	29.98	0.87	13.46
MULTAN	2014	14.11	85.70	36.29	1.56	17.64	25.45	0.27	10.68
KHANEWAL	2004	47.32	98.69	64.08	8.91	33.47	39.86	2.35	20.18
KHANEWAL	2006	45.61	98.47	62.11	7.25	33.19	40.95	1.70	20.71
KHANEWAL	2008	51.58	96.53	59.00	10.58	29.40	37.29	2.93	17.35
KHANEWAL	2010	30.92	96.05	51.65	4.27	26.50	35.28	0.88	16.48
KHANEWAL	2012	30.09	96.27	50.62	4.69	24.98	33.90	1.05	15.05
KHANEWAL	2014	13.57	94.01	40.59	1.82	19.33	28.84	0.37	11.77
PAKPATTAN	2004	43.78	98.83	70.63	7.49	38.48	44.19	1.78	23.55
PAKPATTAN	2006	44.11	98.94	62.56	7.59	33.21	40.97	1.80	20.71
PAKPATTAN	2008	56.68	97.65	63.01	10.89	30.40	37.02	2.91	16.92
PAKPATTAN	2010	35.53	97.30	59.13	5.25	30.59	38.05	1.11	18.53
PAKPATTAN	2012	33.09	97.97	51.51	5.09	25.67	34.94	1.18	15.64
PAKPATTAN	2014	15.33	96.47	42.95	1.43	19.25	28.93	0.23	11.22
LODHRAN	2004	57.98	99.84	76.53	11.62	42.41	47.55	3.41	26.26
LODHRAN	2006	49.53	99.10	70.27	9.63	38.05	44.60	2.54	23.60
LODHRAN	2008	55.06	98.98	59.85	11.64	30.14	38.63	3.38	18.01
LODHRAN	2010	35.71	98.00	63.37	5.18	31.71	38.57	1.04	18.40
LODHRAN	2012	32.65	97.86	54.59	5.24	28.52	37.39	1.21	17.86
LODHRAN	2014	16.47	97.19	47.09	1.78	23.28	32.50	0.31	14.22
DERAGHAZIKHAN	2004	59.87	98.98	75.32	12.22	45.75	50.25	3.44	30.36
DERAGHAZIKHAN	2006	58.40	98.80	76.73	12.07	45.55	50.10	3.28	29.76
DERAGHAZIKHAN	2008	71.29	99.00	77.87	18.63	47.33	51.74	6.28	31.90
DERAGHAZIKHAN	2010	56.85	98.31	79.74	10.12	48.79	52.60	2.32	32.56
DERAGHAZIKHAN	2012	55.56	97.23	66.71	10.41	35.46	41.69	2.60	21.38
DERAGHAZIKHAN	2014	36.28	94.78	64.11	4.95	35.49	41.34	0.99	22.44
RAJANPUR	2004	59.79	99.83	78.28	10.82	47.68	52.37	2.77	32.10
RAJANPUR	2006	75.57	99.86	89.98	19.14	60.71	63.03	5.94	43.86
RAJANPUR	2008	81.04	99.84	86.99	19.49	51.50	54.36	5.97	32.84
RAJANPUR	2010	64.09	99.36	76.36	12.17	45.23	49.67	2.98	29.27
RAJANPUR	2012	55.65	99.51	69.18	11.74	38.24	44.45	3.32	24.21

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
RAJANPUR	2014	33.67	98.94	64.15	4.04	35.75	42.61	0.69	22.81
LAYYAH	2004	46.82	99.24	66.06	7.67	38.19	44.19	1.85	24.80
LAYYAH	2006	45.34	99.50	58.08	7.55	30.43	38.99	1.70	19.13
LAYYAH	2008	55.04	99.09	62.50	9.97	30.87	37.71	2.60	17.68
LAYYAH	2010	42.61	99.16	52.98	7.74	27.44	35.88	1.96	17.27
LAYYAH	2012	25.39	98.93	46.22	3.29	22.20	31.85	0.65	13.36
LAYYAH	2014	11.18	95.91	45.13	0.92	21.36	31.36	0.11	12.95
MUZAFFARGARH	2004	63.42	98.20	79.47	13.32	45.80	49.43	3.75	28.73
MUZAFFARGARH	2006	60.28	99.40	81.68	13.20	49.08	52.66	3.74	32.14
MUZAFFARGARH	2008	64.26	99.28	73.60	16.23	41.44	46.40	5.36	25.65
MUZAFFARGARH	2010	51.40	98.29	72.79	8.46	40.28	45.74	1.93	24.88
MUZAFFARGARH	2012	38.18	96.91	63.69	6.31	33.61	40.14	1.55	20.27
MUZAFFARGARH	2014	29.90	97.91	64.52	4.12	33.82	40.25	0.82	20.16
BAHAWALPUR	2004	47.97	97.27	65.81	9.23	37.23	43.13	2.47	23.79
BAHAWALPUR	2006	50.78	96.00	65.13	10.36	35.74	41.75	2.83	22.20
BAHAWALPUR	2008	55.23	95.12	60.63	13.39	32.84	39.54	4.58	20.36
BAHAWALPUR	2010	34.85	93.26	54.61	5.28	29.31	36.11	1.14	18.36
BAHAWALPUR	2012	37.29	93.72	56.34	6.73	30.68	37.36	1.71	19.22
BAHAWALPUR	2014	22.21	94.53	53.49	2.95	27.86	35.29	0.60	17.01
BAHAWALNAGAR	2004	35.69	98.81	62.00	6.34	32.99	40.79	1.61	20.53
BAHAWALNAGAR	2006	44.44	97.61	57.92	8.43	30.33	37.89	2.15	18.61
BAHAWALNAGAR	2008	58.06	99.35	59.38	11.98	29.70	37.79	3.37	17.56
BAHAWALNAGAR	2010	35.70	98.13	52.82	5.37	27.54	36.03	1.17	17.10
BAHAWALNAGAR	2012	28.14	98.42	46.65	4.61	22.82	32.72	1.08	13.96
BAHAWALNAGAR	2014	16.06	97.96	50.73	1.75	24.76	33.51	0.35	14.67
RAHIMYARKHAN	2004	59.13	97.17	71.51	12.97	41.58	46.39	3.92	26.92
RAHIMYARKHAN	2006	61.25	98.97	77.03	12.50	43.90	48.39	3.33	27.59
RAHIMYARKHAN	2008	61.64	98.80	63.26	15.62	34.91	42.03	5.35	22.03
RAHIMYARKHAN	2010	39.82	97.11	60.39	6.61	32.37	39.09	1.49	19.89
RAHIMYARKHAN	2012	46.98	97.85	61.49	9.21	32.98	40.08	2.54	20.37
RAHIMYARKHAN	2014	28.76	96.53	57.13	4.10	29.28	36.61	0.88	17.50
SINDH									
KHAIRPUR	2004	45.85	98.21	77.22	8.53	44.00	48.22	2.25	27.67
KHAIRPUR	2006	61.07	96.88	74.25	11.48	42.46	47.02	2.91	27.15
KHAIRPUR	2008	69.15	95.31	60.04	15.62	30.55	37.52	4.55	18.09
KHAIRPUR	2010	43.36	97.44	63.61	5.37	33.56	39.74	0.91	20.26
KHAIRPUR	2012	48.15	94.50	57.10	7.23	28.60	35.64	1.47	16.92
KHAIRPUR	2014	26.59	96.85	53.78	3.41	27.71	35.33	0.67	16.91
SUKHUR	2004	29.10	94.56	52.87	4.78	28.54	36.02	1.20	18.12
SUKHUR	2006	43.24	94.04	57.09	9.25	34.66	40.69	2.62	24.07
SUKHUR	2008	58.49	93.47	56.36	13.39	31.30	37.56	4.01	20.09
SUKHUR	2010	33.36	89.68	51.27	4.01	27.04	33.12	0.69	16.59
SUKHUR	2012	36.58	84.80	44.68	6.29	24.19	30.07	1.43	15.25
SUKHUR	2014	26.15	85.35	39.59	3.70	20.26	27.58	0.72	12.56
NAWABSHAH	2004	42.19	98.25	68.52	7.89	38.20	43.06	2.14	23.61
NAWABSHAH	2006	53.15	98.50	73.82	9.98	42.94	48.06	2.43	27.87
NAWABSHAH	2008	64.97	97.89	71.97	13.41	40.57	45.60	3.62	25.31
NAWABSHAH	2010	29.95	96.70	66.31	3.25	36.72	41.83	0.51	22.68
NAWABSHAH	2012	42.59	97.10	72.52	5.85	41.22	45.74	1.10	25.62

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
NAWABSHAH	2014	8.96	92.59	59.32	0.77	31.70	37.85	0.11	19.22
NAUSHAHROFIROZ	2004	43.49	99.65	75.60	8.62	41.46	46.67	2.37	25.28
NAUSHAHROFIROZ	2006	51.13	98.66	65.91	9.60	35.40	42.33	2.55	21.98
NAUSHAHROFIROZ	2008	61.00	96.79	52.89	10.79	26.16	35.15	2.60	15.76
NAUSHAHROFIROZ	2010	33.96	98.23	59.65	4.65	31.39	38.69	0.92	19.27
NAUSHAHROFIROZ	2012	40.61	97.51	57.35	5.39	30.78	38.73	1.03	19.41
NAUSHAHROFIROZ	2014	12.59	98.05	43.41	1.35	21.36	33.62	0.19	14.26
GHOTKI	2004	35.10	99.29	75.62	6.49	43.60	48.59	1.75	27.92
GHOTKI	2006	66.12	99.54	84.05	12.81	51.23	54.42	3.22	33.81
GHOTKI	2008	80.62	97.82	74.56	18.59	40.61	45.57	5.47	24.80
GHOTKI	2010	41.47	97.63	68.46	5.09	36.08	42.13	0.83	21.47
GHOTKI	2012	52.95	97.23	68.69	7.83	37.08	42.11	1.64	22.33
GHOTKI	2014	41.51	96.92	69.67	5.20	37.59	42.66	0.90	22.68
JAKOBABAD	2004	44.48	96.25	78.24	6.95	43.49	46.86	1.53	26.23
JAKOBABAD	2006	76.70	99.29	90.42	17.59	57.94	59.54	5.05	39.20
JAKOBABAD	2008	76.81	98.49	73.38	17.86	39.21	44.08	5.29	23.38
JAKOBABAD	2010	50.27	97.96	75.73	6.82	41.45	45.69	1.29	25.29
JAKOBABAD	2012	59.66	97.85	73.05	10.48	40.12	44.73	2.38	24.42
JAKOBABAD	2014	41.15	98.04	73.80	5.69	42.51	46.73	1.10	26.96
SHIKARPUR	2004	47.32	97.80	62.22	9.21	34.86	41.55	2.81	22.34
SHIKARPUR	2006	67.28	98.54	82.80	14.61	51.97	55.07	4.04	34.86
SHIKARPUR	2008	69.23	95.29	65.82	17.04	34.54	39.83	5.30	20.32
SHIKARPUR	2010	48.54	96.56	64.36	6.86	36.28	41.94	1.55	23.07
SHIKARPUR	2012	51.38	94.75	60.26	8.38	30.70	37.27	1.86	17.99
SHIKARPUR	2014	38.16	96.22	61.26	5.22	33.84	39.76	0.98	21.41
LARKANA	2004	61.00	99.09	83.45	12.66	49.26	52.54	3.53	31.74
LARKANA	2006	56.24	98.97	76.02	11.96	45.10	49.95	3.34	29.50
LARKANA	2008	69.84	98.81	73.57	18.02	42.44	48.02	5.92	27.30
LARKANA	2010	46.01	96.25	61.46	6.25	31.36	37.34	1.20	18.33
LARKANA	2012	48.94	95.98	56.44	7.80	28.70	35.33	1.70	17.04
LARKANA	2014	27.31	96.18	56.85	3.33	29.52	36.62	0.60	18.01
DADU	2004	54.90	99.35	82.58	10.65	48.09	51.70	2.81	30.58
DADU	2006	64.29	99.35	76.61	13.32	45.71	50.47	3.64	30.26
DADU	2008	68.51	98.29	59.79	13.56	33.04	41.00	3.67	21.71
DADU	2010	31.76	98.36	65.62	3.87	33.97	40.80	0.70	20.49
DADU	2012	38.04	97.35	65.35	5.45	34.70	40.89	1.12	21.02
DADU	2014	11.27	95.96	53.25	1.34	26.82	35.98	0.22	16.71
HYDERABAD	2004	28.47	93.97	58.37	4.79	30.90	37.45	1.13	18.75
HYDERABAD	2006	37.86	89.93	49.02	7.04	25.25	31.96	1.80	15.37
HYDERABAD	2008	41.41	87.78	48.32	8.32	26.04	33.42	2.26	16.63
HYDERABAD	2010	21.07	84.76	43.93	2.62	24.83	31.10	0.48	16.33
HYDERABAD	2012	28.07	83.58	43.31	4.27	23.49	29.62	0.89	14.94
HYDERABAD	2014	16.93	83.68	46.03	1.98	25.10	30.64	0.33	15.73
BADIN	2004	47.27	97.18	77.21	8.55	42.17	45.94	2.33	25.23
BADIN	2006	70.59	99.77	85.21	15.21	48.63	51.48	4.06	30.19
BADIN	2008	69.50	98.95	78.42	14.83	43.45	47.56	4.19	26.49
BADIN	2010	47.97	98.85	82.88	6.56	48.74	52.01	1.20	31.29
BADIN	2012	55.49	97.73	84.16	8.56	50.04	52.87	1.74	32.19
BADIN	2014	28.67	97.07	75.25	3.43	44.24	47.92	0.60	28.32

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
THATTA	2004	58.11	99.19	84.26	12.36	49.82	52.84	3.69	32.03
THATTA	2006	65.68	98.85	86.58	14.22	52.96	55.60	4.00	34.95
THATTA	2008	67.63	94.62	76.62	15.20	43.68	47.41	4.51	27.27
THATTA	2010	50.04	96.88	77.49	6.46	44.53	48.61	1.17	28.05
THATTA	2012	34.03	97.44	78.33	4.75	45.08	48.80	0.95	28.33
THATTA	2014	24.93	96.83	80.40	3.05	45.32	48.50	0.56	27.71
SANGHAR	2004	42.00	98.21	75.79	7.53	46.27	50.61	1.95	30.88
SANGHAR	2006	56.43	98.10	75.70	10.87	45.77	49.98	2.75	30.49
SANGHAR	2008	62.90	96.86	62.21	13.25	35.25	41.25	3.70	22.84
SANGHAR	2010	30.28	97.02	59.76	3.48	32.29	38.99	0.58	19.99
SANGHAR	2012	38.19	94.78	58.59	6.04	32.69	39.14	1.31	20.89
SANGHAR	2014	17.37	94.29	66.65	1.77	39.28	43.71	0.26	25.37
MIRPHURKHAS	2004	42.38	97.27	70.08	7.84	41.52	46.82	2.04	27.54
MIRPHURKHAS	2006	51.73	98.89	77.85	10.02	47.19	51.77	2.54	31.63
MIRPHURKHAS	2008	64.80	97.92	74.72	14.11	44.52	49.45	4.07	29.42
MIRPHURKHAS	2010	41.77	97.31	69.43	5.80	38.18	43.92	1.09	23.82
MIRPHURKHAS	2012	46.02	97.44	77.06	6.57	47.35	51.04	1.31	31.79
MIRPHURKHAS	2014	24.86	97.96	75.73	2.83	45.64	49.81	0.47	30.30
THARPARKAR	2004	41.14	99.63	84.38	6.74	54.21	56.90	1.61	37.22
THARPARKAR	2006	70.63	100.00	94.82	13.38	62.94	64.03	3.28	43.96
THARPARKAR	2008	72.87	99.95	92.23	13.98	55.06	56.95	3.60	35.27
THARPARKAR	2010	50.33	99.88	92.79	5.53	57.43	59.11	0.88	37.63
THARPARKAR	2012	53.07	99.49	85.75	7.67	51.22	54.11	1.52	33.35
THARPARKAR	2014	31.71	100.00	87.77	3.22	49.94	52.87	0.49	30.91
KARACHI	2004	9.08	72.61	15.33	1.13	7.07	15.43	0.23	5.10
KARACHI	2006	7.27	65.81	13.57	1.04	6.45	13.82	0.24	4.78
KARACHI	2008	10.22	54.31	10.34	1.65	4.56	10.59	0.41	3.26
KARACHI	2010	2.84	55.14	10.32	0.24	4.56	10.84	0.03	3.31
KARACHI	2012	2.38	47.91	7.07	0.22	3.07	8.41	0.03	2.39
KARACHI	2014	0.95	51.67	4.89	0.13	2.08	7.83	0.03	1.97
KYBER PAKHTUNKHWA									
SWAT	2004	54.61	99.38	74.47	9.71	41.93	47.14	2.41	26.25
SWAT	2006	36.27	98.82	64.22	5.27	33.75	40.85	1.14	20.51
SWAT	2008	61.16	98.04	71.67	10.75	40.82	45.48	2.54	26.11
SWAT	2010	33.47	97.48	59.68	3.98	32.47	40.03	0.68	20.85
SWAT	2012	20.92	97.95	50.58	2.11	24.65	33.92	0.33	14.96
SWAT	2014	5.69	95.52	55.92	0.64	27.79	36.01	0.09	16.47
DIR	2004	57.09	100.00	75.42	10.53	43.31	48.72	2.59	27.75
DIR	2006	54.44	100.00	79.93	8.93	47.47	51.49	1.98	30.86
DIR	2008	71.19	100.00	77.61	12.46	43.99	49.16	2.95	27.68
DIR	2010	30.95	99.56	65.83	3.43	34.53	42.00	0.58	21.17
DIR	2012	33.33	99.63	71.65	3.52	39.42	45.37	0.56	24.62
DIR	2014	6.11	98.83	59.35	0.60	31.99	40.17	0.10	20.50
CHITRAL	2004	35.79	99.83	68.39	5.38	35.52	42.66	1.15	21.47
CHITRAL	2006	30.74	100.00	61.22	3.63	30.31	38.66	0.64	17.84
CHITRAL	2008	41.49	99.46	56.70	5.10	28.24	37.21	0.97	17.32
CHITRAL	2010	15.91	99.84	55.78	1.34	27.56	36.78	0.17	16.62
CHITRAL	2012	8.12	100.00	33.86	0.64	16.17	27.90	0.09	10.84
CHITRAL	2014	0.48	99.87	45.58	0.00	20.60	31.03	0.00	12.14

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
SHANGLA	2004	66.20	100.00	85.63	13.13	54.42	57.63	3.48	37.72
SHANGLA	2006	61.21	100.00	84.67	10.45	53.61	57.50	2.45	36.88
SHANGLA	2008	66.51	100.00	79.00	9.82	42.90	47.35	2.04	25.62
SHANGLA	2010	41.99	99.94	73.19	4.79	38.88	44.68	0.78	23.32
SHANGLA	2012	36.56	100.00	74.77	5.05	41.65	47.06	0.94	26.23
SHANGLA	2014	4.25	100.00	84.75	0.39	47.66	51.04	0.06	29.40
MALAKAND	2004	60.59	99.71	71.35	11.96	38.68	44.24	3.22	23.87
MALAKAND	2006	48.27	98.52	68.54	7.32	35.90	42.34	1.67	21.50
MALAKAND	2008	55.62	98.87	52.22	10.00	25.80	35.11	2.49	15.71
MALAKAND	2010	24.09	97.33	55.35	2.93	27.08	34.17	0.51	15.54
MALAKAND	2012	19.09	96.52	33.67	2.04	15.82	26.23	0.33	10.09
MALAKAND	2014	2.92	97.18	37.55	0.21	17.53	28.83	0.03	11.23
BUNER	2004	70.26	100.00	86.78	13.30	52.96	55.97	3.42	35.09
BUNER	2006	63.98	100.00	79.55	11.28	42.99	47.90	2.75	26.18
BUNER	2008	74.85	99.55	77.55	13.38	38.94	44.06	3.33	22.05
BUNER	2010	55.66	99.91	80.61	9.67	42.87	47.59	2.27	25.49
BUNER	2012	41.57	100.00	61.60	5.70	32.94	40.21	1.08	20.37
BUNER	2014	16.41	100.00	72.17	1.99	38.20	44.44	0.34	23.14
PESHAWAR	2004	43.17	88.83	55.92	8.18	29.69	35.34	2.20	17.88
PESHAWAR	2006	42.62	94.06	54.38	6.79	27.25	34.66	1.47	16.20
PESHAWAR	2008	43.76	83.79	42.87	7.48	21.06	28.52	1.81	12.63
PESHAWAR	2010	22.20	83.20	36.62	3.06	17.04	25.21	0.74	10.19
PESHAWAR	2012	14.77	79.04	22.81	1.50	10.63	19.98	0.23	7.26
PESHAWAR	2014	4.25	79.03	31.61	0.31	14.79	22.94	0.04	8.98
CHARSADDA	2004	56.01	98.57	70.03	10.78	38.03	43.79	2.76	23.43
CHARSADDA	2006	45.54	96.91	70.37	6.82	36.47	41.67	1.40	21.22
CHARSADDA	2008	59.27	97.18	66.60	9.06	35.81	41.37	1.95	21.57
CHARSADDA	2010	24.72	95.55	53.97	3.10	26.76	34.79	0.54	15.85
CHARSADDA	2012	27.19	95.71	47.83	3.15	23.62	32.79	0.54	14.55
CHARSADDA	2014	7.15	93.50	44.56	0.54	21.54	31.00	0.07	13.26
NOWSHERA	2004	43.15	96.55	61.96	6.56	31.96	38.81	1.48	19.08
NOWSHERA	2006	24.68	96.24	50.59	3.06	24.72	33.54	0.56	14.73
NOWSHERA	2008	41.74	95.86	41.70	6.13	19.44	29.70	1.31	11.93
NOWSHERA	2010	25.75	96.45	47.01	3.33	21.90	31.15	0.60	12.89
NOWSHERA	2012	19.37	93.72	34.72	2.30	16.91	26.89	0.44	11.15
NOWSHERA	2014	3.51	92.00	37.67	0.25	16.93	26.38	0.03	10.08
KOHAT	2004	50.15	96.26	61.42	8.29	31.89	38.29	1.83	19.25
KOHAT	2006	37.62	95.39	61.17	6.01	31.07	37.63	1.34	18.19
KOHAT	2008	53.00	92.48	52.38	8.88	25.47	33.21	2.13	14.97
KOHAT	2010	25.02	94.04	58.78	3.71	31.36	37.72	0.76	19.14
KOHAT	2012	23.91	93.78	45.56	3.21	23.07	31.49	0.61	14.28
KOHAT	2014	5.26	94.44	48.19	0.94	24.63	32.78	0.28	15.08
KARAK	2004	54.67	99.82	69.74	10.10	38.74	45.33	2.49	24.40
KARAK	2006	54.15	99.96	69.77	8.01	37.99	44.74	1.59	23.78
KARAK	2008	60.81	99.92	68.96	10.27	39.72	45.98	2.34	26.11
KARAK	2010	47.46	99.39	75.79	7.29	44.18	49.67	1.53	28.96
KARAK	2012	28.43	97.33	53.03	3.27	26.63	36.13	0.61	16.52
KARAK	2014	8.62	98.27	52.05	1.01	27.07	36.95	0.20	17.49
HANGU	2004	48.31	98.86	68.86	10.11	37.07	43.55	2.81	22.81

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
HANGU	2006	51.09	99.97	73.56	9.20	37.86	43.21	2.64	22.00
HANGU	2008	70.28	100.00	57.17	12.33	28.35	37.78	3.00	17.39
HANGU	2010	38.93	98.96	64.54	6.47	32.61	39.63	1.52	19.01
HANGU	2012	37.53	98.72	67.97	4.69	34.20	40.00	0.85	19.35
HANGU	2014	5.02	97.29	55.80	0.47	27.36	36.32	0.08	16.22
DERAISMAILKHAN	2004	58.45	99.31	72.47	11.66	39.01	44.08	3.16	23.08
DERAISMAILKHAN	2006	62.42	99.90	83.05	10.42	47.77	51.49	2.57	29.81
DERAISMAILKHAN	2008	68.16	99.65	72.99	13.42	41.17	45.95	3.48	25.59
DERAISMAILKHAN	2010	36.46	99.68	75.56	4.92	41.80	46.61	0.97	25.44
DERAISMAILKHAN	2012	47.77	99.31	70.97	7.24	40.24	45.55	1.42	25.29
DERAISMAILKHAN	2014	12.68	98.29	67.14	1.34	37.78	43.58	0.22	24.06
TANK	2004	61.16	99.95	86.25	11.44	46.39	49.17	3.06	27.09
TANK	2006	70.52	100.00	80.62	13.62	45.39	49.55	3.34	28.04
TANK	2008	68.04	100.00	79.01	12.30	41.50	46.02	3.08	24.14
TANK	2010	38.71	100.00	80.16	5.86	43.56	47.39	1.21	25.85
TANK	2012	48.19	99.49	80.54	6.72	45.01	48.80	1.38	27.69
TANK	2014	17.49	99.08	73.12	2.02	40.88	46.20	0.33	25.62
MANSEHRA	2004	40.21	98.75	65.59	5.67	35.53	42.35	1.23	22.25
MANSEHRA	2006	31.65	99.23	67.24	4.80	35.48	42.32	1.06	21.74
MANSEHRA	2008	39.94	99.23	53.34	5.24	28.72	38.06	0.99	18.76
MANSEHRA	2010	19.85	97.96	55.21	2.07	30.78	38.88	0.34	20.41
MANSEHRA	2012	19.60	96.43	56.36	2.04	30.64	38.81	0.33	19.75
MANSEHRA	2014	2.76	98.28	52.27	0.25	29.50	38.23	0.03	20.07
ABBOTTABAD	2004	28.30	95.41	48.74	3.42	23.95	32.64	0.66	14.46
ABBOTTABAD	2006	10.89	94.38	50.44	1.39	24.05	32.98	0.24	14.10
ABBOTTABAD	2008	14.13	92.69	39.94	1.37	18.49	29.41	0.21	11.57
ABBOTTABAD	2010	15.11	91.85	42.56	1.63	20.50	29.69	0.28	12.61
ABBOTTABAD	2012	6.27	89.07	26.95	0.40	11.70	22.03	0.03	7.60
ABBOTTABAD	2014	0.00	91.39	32.96	0.00	15.07	25.96	0.00	9.59
BATTAGRAM	2004	55.64	100.00	85.94	8.22	48.22	51.49	1.75	29.41
BATTAGRAM	2006	53.25	100.00	86.01	8.93	52.00	55.23	2.04	34.44
BATTAGRAM	2008	60.54	99.81	69.20	9.49	34.80	41.79	2.04	20.27
BATTAGRAM	2010	27.31	100.00	58.39	3.30	28.86	38.17	0.55	17.66
BATTAGRAM	2012	31.39	100.00	71.15	3.14	38.31	44.37	0.47	23.61
BATTAGRAM	2014	6.83	100.00	78.00	0.45	45.27	50.03	0.05	29.24
KOHISTAN	2004	52.16	100.00	97.38	9.88	61.36	62.06	2.58	41.19
KOHISTAN	2006	54.37	100.00	98.37	8.29	65.24	65.66	1.75	44.83
KOHISTAN	2008	70.24	100.00	99.62	9.78	69.75	69.83	1.88	50.42
KOHISTAN	2010	35.12	100.00	97.62	3.70	63.27	63.84	0.61	42.80
KOHISTAN	2012	46.98	100.00	98.68	5.88	66.70	67.02	1.05	46.43
KOHISTAN	2014	6.71	100.00	96.49	0.69	61.13	62.03	0.11	41.11
HARIPUR	2004	29.27	96.75	56.29	4.14	30.21	37.92	0.87	19.07
HARIPUR	2006	14.28	98.81	52.23	1.86	26.30	36.29	0.40	16.45
HARIPUR	2008	17.09	93.03	33.58	1.73	16.40	27.61	0.26	11.23
HARIPUR	2010	12.03	96.76	28.95	1.14	12.33	25.33	0.17	8.43
HARIPUR	2012	6.11	95.43	29.79	0.73	13.97	26.57	0.12	9.96
HARIPUR	2014	2.59	93.60	26.43	0.08	11.79	23.37	0.00	7.93
BANNU	2004	47.91	99.49	73.29	8.37	37.71	43.97	1.99	22.41
BANNU	2006	51.89	99.63	78.62	8.81	43.73	48.31	1.96	26.94

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
BANNU	2008	63.75	99.74	71.88	10.49	36.41	41.94	2.35	20.99
BANNU	2010	27.11	99.47	76.73	3.49	39.36	44.66	0.72	22.73
BANNU	2012	43.52	99.49	73.33	6.22	38.02	43.31	1.98	22.01
BANNU	2014	4.45	99.89	60.46	0.37	30.84	39.03	0.04	18.53
LAKKIMARWAT	2004	63.92	99.92	81.19	12.57	48.05	52.07	3.40	31.24
LAKKIMARWAT	2006	54.89	99.88	81.91	9.12	47.01	51.10	2.05	29.62
LAKKIMARWAT	2008	65.88	100.00	73.36	11.01	40.90	46.60	2.50	25.69
LAKKIMARWAT	2010	46.40	98.44	83.62	5.72	49.77	53.03	1.01	31.96
LAKKIMARWAT	2012	44.38	99.27	65.30	5.64	35.74	43.05	1.02	22.81
LAKKIMARWAT	2014	6.23	100.00	65.96	0.66	34.61	41.03	0.10	20.70
MARDAN	2004	56.72	96.80	58.71	10.68	29.36	36.88	2.88	17.18
MARDAN	2006	46.18	97.45	56.73	6.88	27.47	35.63	1.37	16.08
MARDAN	2008	52.55	97.33	51.99	9.17	25.71	34.64	2.20	15.51
MARDAN	2010	28.91	95.29	53.53	4.03	27.48	35.04	0.79	16.78
MARDAN	2012	17.65	94.34	49.62	1.84	23.75	31.88	0.28	13.75
MARDAN	2014	4.11	94.39	34.18	0.38	15.63	26.14	0.05	9.77
SWABI	2004	42.97	98.92	60.45	7.09	31.50	38.46	1.63	18.99
SWABI	2006	42.86	99.70	69.70	6.71	37.28	43.72	1.43	22.63
SWABI	2008	49.86	99.47	50.25	7.44	23.87	33.02	1.59	14.10
SWABI	2010	25.70	97.69	47.49	3.35	24.26	33.62	0.70	15.49
SWABI	2012	17.46	97.87	44.31	1.81	20.30	30.00	0.30	11.83
SWABI	2014	1.52	95.85	44.26	0.10	21.37	32.41	0.01	13.65
BALOCHISTAN									
QUETTA	2004	16.55	96.06	53.47	1.98	27.35	35.34	0.36	16.67
QUETTA	2006	46.02	91.32	47.70	7.76	25.03	33.02	1.83	15.63
QUETTA	2008	52.01	84.65	36.05	9.61	17.38	25.70	2.34	10.68
QUETTA	2010	3.11	88.30	39.45	0.22	17.23	25.60	0.02	9.64
QUETTA	2012	7.30	88.03	29.59	0.56	13.39	23.90	0.07	8.64
QUETTA	2014	11.87	94.35	49.85	1.91	23.28	32.32	0.43	13.54
PISHIN	2004	37.62	99.89	81.40	5.21	42.67	46.65	1.20	24.61
PISHIN	2006	81.50	100.00	88.59	17.83	51.74	54.50	4.89	32.66
PISHIN	2008	81.59	99.84	78.65	18.26	43.40	48.41	4.99	26.85
PISHIN	2010	2.06	99.69	85.28	0.19	42.08	44.96	0.02	22.50
PISHIN	2012	29.98	99.01	73.17	3.42	41.16	47.07	0.58	25.95
PISHIN	2014	15.48	99.39	82.97	1.69	47.54	51.29	0.26	29.63
QILLAABDULLAH	2004	42.79	99.41	91.09	5.89	54.42	56.23	1.10	34.80
QILLAABDULLAH	2006	80.23	100.00	95.30	20.91	64.63	65.84	6.57	46.10
QILLAABDULLAH	2008	89.67	99.33	92.71	24.12	57.27	58.69	7.60	37.73
QILLAABDULLAH	2010	7.14	99.85	92.09	0.60	51.40	53.09	0.08	30.37
QILLAABDULLAH	2012	69.36	100.00	93.73	10.86	58.56	60.04	2.52	38.90
QILLAABDULLAH	2014	41.67	100.00	97.44	6.89	67.02	67.68	1.69	47.65
CHAGAI	2004	49.45	100.00	87.62	6.94	51.72	54.44	1.36	33.45
CHAGAI	2006	84.51	100.00	91.78	19.05	60.46	62.46	5.30	42.57
CHAGAI	2008	85.88	100.00	87.09	18.41	50.91	54.11	4.87	32.63
CHAGAI	2010	26.66	100.00	85.50	1.76	53.99	56.16	0.17	36.45
CHAGAI	2012	39.69	98.54	80.74	4.42	45.66	49.11	0.72	28.49
CHAGAI	2014	12.15	99.58	80.35	1.04	46.67	50.99	0.12	30.44
SIBI	2004	28.05	97.74	74.93	3.36	43.58	48.04	0.55	28.56
SIBI	2006	72.28	98.85	74.21	18.44	45.61	50.03	5.97	31.30

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
SIBI	2008	79.35	99.08	70.66	17.98	41.90	47.74	4.83	27.79
SIBI	2010	6.58	93.54	60.43	0.61	33.75	39.69	0.09	21.24
SIBI	2012	31.12	97.80	64.55	3.57	34.70	41.13	0.58	21.43
SIBI	2014	26.31	97.96	76.15	3.10	49.42	53.57	0.54	34.88
ZIARAT	2004	25.15	98.50	87.71	2.26	48.40	51.01	0.30	28.68
ZIARAT	2006	68.45	99.21	81.49	13.54	44.71	48.59	3.56	27.23
ZIARAT	2008	70.59	100.00	88.67	9.66	43.99	46.74	2.00	23.49
ZIARAT	2010	4.00	99.24	84.27	0.20	46.93	50.21	0.02	28.06
ZIARAT	2012	34.14	98.81	62.87	2.99	31.36	38.82	0.39	18.30
ZIARAT	2014	49.28	99.84	90.57	6.74	60.29	62.41	1.31	42.84
KOHLU	2004								
KOHLU	2006	88.54	99.04	94.40	20.11	70.01	70.84	5.38	53.47
KOHLU	2008	94.79	100.00	97.29	18.63	61.70	62.44	4.17	40.41
KOHLU	2010	23.15	100.00	96.88	2.25	61.88	62.63	0.32	41.15
KOHLU	2012	50.41	100.00	99.09	5.06	71.48	71.69	0.75	53.08
KOHLU	2014	14.86	100.00	87.03	1.17	51.48	54.05	0.14	33.00
DERABUGTI	2004								
DERABUGTI	2006	88.97	100.00	98.95	19.08	70.97	71.19	5.24	52.90
DERABUGTI	2008	96.28	100.00	97.76	24.79	66.27	66.71	7.43	47.81
DERABUGTI	2010	27.50	100.00	98.32	1.86	69.66	70.03	0.19	50.81
DERABUGTI	2012	58.79	100.00	95.91	6.25	64.66	65.58	0.91	45.42
DERABUGTI	2014	46.77	99.74	89.36	6.00	53.40	55.42	1.09	33.78
KALAT	2004	27.08	99.70	90.03	2.70	52.48	54.46	0.40	33.22
KALAT	2006	70.00	99.49	75.78	14.01	39.84	44.56	3.80	23.32
KALAT	2008	91.75	99.77	91.04	21.55	56.53	58.29	5.97	36.94
KALAT	2010	12.92	98.88	71.53	0.86	36.28	42.19	0.08	21.15
KALAT	2012	34.16	99.15	78.90	3.47	39.42	43.95	0.50	21.56
KALAT	2014	7.98	95.25	58.04	0.47	28.50	35.57	0.05	16.57
MASTUNG	2004	31.47	99.39	80.02	3.94	44.46	48.43	0.65	27.44
MASTUNG	2006	54.20	96.58	61.80	9.74	27.32	34.16	2.23	14.18
MASTUNG	2008	89.08	96.67	85.58	23.01	54.62	56.69	6.88	37.07
MASTUNG	2010	6.45	95.88	47.34	0.43	25.08	34.40	0.04	16.45
MASTUNG	2012	34.52	95.53	56.62	3.45	29.67	37.03	0.51	18.10
MASTUNG	2014	20.07	92.70	63.65	1.66	32.22	38.08	0.19	18.88
KHUZDAR	2004	26.38	99.94	89.14	2.56	54.72	57.08	0.42	35.89
KHUZDAR	2006	75.10	99.78	81.40	15.16	44.33	48.28	3.83	26.62
KHUZDAR	2008	85.71	96.70	85.16	20.45	51.64	53.84	5.44	33.03
KHUZDAR	2010	15.34	99.71	71.77	1.02	38.02	43.40	0.11	22.70
KHUZDAR	2012	33.64	99.50	73.67	3.63	41.22	46.50	0.53	25.69
KHUZDAR	2014	19.29	100.00	59.54	1.94	30.45	38.24	0.25	18.33
AWARAN	2004	32.50	100.00	91.98	3.52	52.65	54.63	0.55	32.18
AWARAN	2006	57.01	100.00	90.26	8.21	51.25	53.59	1.55	31.12
AWARAN	2008	85.58	100.00	84.16	16.19	52.13	55.85	4.00	35.38
AWARAN	2010	12.08	100.00	62.44	0.61	31.04	39.77	0.05	18.74
AWARAN	2012	38.75	100.00	94.67	3.88	57.53	58.83	0.57	36.82
AWARAN	2014	37.63	100.00	77.72	2.58	42.62	47.62	0.31	25.97
KHARAN	2004	30.00	100.00	92.26	3.18	51.61	53.38	0.47	30.85
KHARAN	2006	74.72	100.00	87.80	13.21	49.81	52.83	3.03	30.99
KHARAN	2008	93.14	100.00	91.08	21.13	52.22	54.33	5.66	32.07

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
KHARAN	2010	17.59	100.00	82.76	0.84	44.92	48.85	0.07	26.57
KHARAN	2012	42.21	100.00	89.53	4.02	51.33	53.97	0.55	31.87
KHARAN	2014	27.26	100.00	81.90	2.73	48.85	52.82	0.40	32.15
LASBELA	2004	37.20	98.49	80.20	4.79	46.21	49.92	0.88	29.19
LASBELA	2006	72.60	100.00	86.92	17.18	51.54	54.24	5.11	33.28
LASBELA	2008	58.31	95.80	77.62	8.66	42.91	46.91	1.89	26.01
LASBELA	2010	23.43	98.80	77.43	1.96	47.09	51.25	0.29	31.76
LASBELA	2012	22.29	97.35	69.49	2.29	39.04	44.73	0.37	24.63
LASBELA	2014	12.44	97.70	68.44	1.33	40.70	45.24	0.20	26.56
KECH	2004	12.77	100.00	84.87	1.27	47.70	51.25	0.18	29.11
KECH	2006	64.16	100.00	86.53	10.65	52.62	55.58	2.31	34.74
KECH	2008	78.74	99.59	78.16	13.22	43.55	47.95	2.70	26.76
KECH	2010	8.66	100.00	87.28	0.38	53.71	56.01	0.03	35.28
KECH	2012	31.71	99.75	66.57	2.80	38.54	44.71	0.34	25.59
KECH	2014								
GWADAR	2004	19.48	98.89	72.26	1.99	42.68	48.15	0.32	27.90
GWADAR	2006	49.98	99.61	72.37	9.41	40.71	45.92	2.27	25.49
GWADAR	2008	53.53	97.30	58.13	8.53	31.33	38.89	1.77	19.97
GWADAR	2010	7.20	100.00	73.84	0.36	40.58	45.56	0.03	25.01
GWADAR	2012	25.15	99.62	52.23	2.75	26.07	34.73	0.42	16.00
GWADAR	2014	5.72	100.00	66.54	0.30	33.10	39.73	0.02	19.08
PANJGUR	2004	28.70	100.00	89.73	3.48	54.42	56.66	0.61	35.39
PANJGUR	2006	75.26	100.00	91.92	13.11	59.52	61.53	2.95	40.99
PANJGUR	2008	78.82	100.00	77.11	13.42	46.61	51.40	2.93	31.19
PANJGUR	2010	4.89	100.00	96.42	0.27	60.17	61.01	0.02	39.19
PANJGUR	2012								
PANJGUR	2014								
ZHOB	2004	36.91	100.00	93.18	4.75	59.86	61.26	0.87	40.57
ZHOB	2006	73.24	100.00	83.06	14.36	49.58	53.06	3.68	31.94
ZHOB	2008	86.03	99.40	83.66	21.57	52.70	55.45	6.40	35.82
ZHOB	2010	14.68	99.67	85.68	1.08	46.61	49.56	0.14	27.96
ZHOB	2012	50.96	99.74	87.48	6.30	54.87	57.46	1.09	37.37
ZHOB	2014	9.37	100.00	85.08	0.62	53.23	56.56	0.07	35.75
LORALAI	2004	32.73	100.00	90.68	3.68	56.06	58.15	0.61	36.68
LORALAI	2006	80.75	100.00	91.20	15.46	56.03	57.93	3.75	36.73
LORALAI	2008	86.85	99.95	87.69	22.26	48.44	51.22	6.52	29.75
LORALAI	2010	37.31	99.36	88.12	3.23	53.64	55.99	0.39	35.32
LORALAI	2012	20.59	99.75	84.15	1.61	49.70	52.54	0.20	31.43
LORALAI	2014	5.89	100.00	70.82	0.35	34.12	40.10	0.03	18.72
BARKHAN	2004	27.16	100.00	93.39	2.99	62.61	64.13	0.55	44.30
BARKHAN	2006	75.33	98.63	89.53	14.14	51.10	52.90	3.36	31.08
BARKHAN	2008	88.82	100.00	85.75	18.88	50.12	53.13	4.67	31.59
BARKHAN	2010	32.43	100.00	93.79	2.32	55.29	56.34	0.28	33.76
BARKHAN	2012	48.57	100.00	94.76	4.69	59.65	60.89	0.64	38.90
BARKHAN	2014	9.89	100.00	94.01	0.74	65.61	66.59	0.09	47.85
MUSAKHEL	2004	27.25	100.00	98.80	2.82	68.25	68.64	0.46	48.58
MUSAKHEL	2006	81.30	100.00	97.52	15.48	57.97	58.54	3.79	36.01
MUSAKHEL	2008	94.40	100.00	95.82	23.09	61.22	62.21	6.60	41.33
MUSAKHEL	2010	52.09	100.00	95.90	4.44	53.04	54.18	0.55	30.50

DISTRICT	YEAR	HH	MDPI HH	MPI HH	PG	MPI_33	MPI_0	SPG	MDPI
MUSAKHEL	2012	27.77	100.00	97.09	2.26	60.08	60.82	0.26	38.55
MUSAKHEL	2014	11.78	100.00	67.96	0.92	36.93	43.38	0.11	22.73
QILLASAIFULLAH	2004	46.52	99.80	95.14	6.14	65.91	66.84	1.16	48.05
QILLASAIFULLAH	2006	87.82	99.44	90.37	20.31	58.39	60.29	5.69	39.92
QILLASAIFULLAH	2008	93.68	100.00	90.75	22.11	56.98	59.17	6.03	37.94
QILLASAIFULLAH	2010	12.82	100.00	90.56	0.86	51.38	53.67	0.09	31.49
QILLASAIFULLAH	2012	52.42	100.00	93.57	6.26	57.69	59.19	1.00	37.45
QILLASAIFULLAH	2014	4.51	100.00	84.45	0.13	42.93	46.95	0.01	23.83
NASIRABAD	2004	21.63	99.98	90.82	2.75	54.21	56.26	0.54	35.12
NASIRABAD	2006	86.30	99.92	96.09	21.74	66.89	67.78	6.54	48.65
NASIRABAD	2008	93.38	99.86	93.39	23.12	54.12	55.64	6.64	33.62
NASIRABAD	2010	30.59	100.00	89.74	2.24	53.60	55.86	0.26	34.66
NASIRABAD	2012	50.19	99.60	87.08	5.85	55.06	57.73	0.92	37.86
NASIRABAD	2014	23.30	98.38	78.86	2.66	43.86	47.80	0.45	26.93
JAFARABAD	2004	19.29	97.32	82.41	1.64	44.24	47.28	0.23	26.10
JAFARABAD	2006	81.52	99.55	89.79	19.64	58.45	60.37	5.86	40.75
JAFARABAD	2008	88.93	99.25	83.15	20.85	45.44	48.49	5.89	26.98
JAFARABAD	2010	26.69	98.82	80.98	2.00	46.00	49.80	0.25	28.41
JAFARABAD	2012	50.81	99.31	81.03	5.57	46.42	50.04	0.82	29.08
JAFARABAD	2014	30.40	99.60	75.91	3.06	42.50	47.11	0.50	26.40
JHALMAGSI	2004	31.93	100.00	97.93	3.31	62.30	62.66	0.57	41.75
JHALMAGSI	2006	89.20	100.00	93.69	20.44	58.42	59.98	5.71	38.71
JHALMAGSI	2008	95.63	100.00	97.27	24.68	62.22	62.71	7.27	41.94
JHALMAGSI	2010	14.79	100.00	87.04	1.00	44.36	47.54	0.10	24.53
JHALMAGSI	2012	34.13	100.00	88.26	3.44	54.93	57.53	0.55	37.28
JHALMAGSI	2014	31.49	100.00	91.40	3.52	55.84	57.61	0.58	36.69
BOLAN	2004	26.24	99.87	88.14	2.59	51.37	53.69	0.43	32.66
BOLAN	2006	77.02	99.87	88.42	18.71	56.63	58.90	6.04	39.45
BOLAN	2008	89.06	100.00	94.07	23.33	61.36	62.71	6.92	41.95
BOLAN	2010	14.73	98.74	81.32	0.86	46.64	50.49	0.07	29.18
BOLAN	2012	47.41	99.58	86.52	5.07	55.58	58.11	0.79	38.46
BOLAN	2014	18.11	100.00	74.60	1.83	43.73	48.14	0.26	28.44

Appendix D

Table D1: Poverty estimates at provincial level

YEAR	PROVINCE	HH	MDPI-HH	MPI-HH	PG	MPI_33	MPI_0	SPG	MDPI
2004	Punjab	37.83	94.44	51.11	6.62	26.60	34.61	1.70	16.58
2006	Punjab	33.58	92.65	48.13	5.88	25.24	33.32	1.45	15.97
2008	Punjab	43.20	91.38	42.31	8.68	21.25	30.02	2.49	13.29
2010	Punjab	24.91	91.16	39.63	3.53	19.96	28.85	0.74	12.65
2012	Punjab	21.33	89.38	35.65	3.35	17.53	26.82	0.79	11.18
2014	Punjab	12.65	88.25	31.63	1.52	15.39	24.39	0.29	9.85
2004	Sindh	34.34	90.66	57.23	6.20	32.27	37.97	1.63	20.62
2006	Sindh	42.22	87.42	55.38	8.43	32.40	37.69	2.23	21.42
2008	Sindh	49.60	84.36	50.89	10.77	27.88	33.73	3.11	17.60
2010	Sindh	29.20	84.07	49.53	3.71	26.88	32.63	0.68	16.82
2012	Sindh	31.89	80.89	47.00	4.83	25.73	31.18	1.01	16.22
2014	Sindh	17.30	81.10	43.69	2.12	23.86	29.77	0.38	15.19
2004	Khyber Pakhtunkhwa	49.79	97.44	67.46	8.89	36.84	42.76	2.23	22.83
2006	Khyber Pakhtunkhwa	44.27	98.07	67.84	7.01	36.77	42.96	1.56	22.73
2008	Khyber Pakhtunkhwa	53.71	96.59	60.61	8.85	32.40	39.46	2.04	20.19
2010	Khyber Pakhtunkhwa	28.47	95.89	57.81	3.69	30.38	37.76	0.72	18.79
2012	Khyber Pakhtunkhwa	25.62	95.07	51.64	3.08	27.00	35.07	0.58	16.95
2014	Khyber Pakhtunkhwa	5.43	94.50	50.22	0.54	25.94	34.37	0.09	16.27
2004	Balochistan	28.48	99.15	83.57	3.37	48.81	52.03	0.60	31.08
2006	Balochistan	71.82	98.37	81.48	15.43	49.98	53.36	4.27	33.41
2008	Balochistan	80.52	97.30	79.01	17.98	46.33	49.95	4.88	29.70
2010	Balochistan	15.98	98.01	77.40	1.15	44.05	48.05	0.13	27.63
2012	Balochistan	36.90	98.00	74.06	4.14	43.35	48.05	0.69	28.14
2014	Balochistan	20.69	98.38	73.15	2.47	41.70	46.79	0.47	26.63

Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI-33, Multidimensional Poverty Index with 33% cut-off; MPI-0, Multidimensional Poverty Index with 0 cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

Table D2: Poverty estimates at national level

YEAR	HH	MDPI-HH	MPI-HH	PG	MPI_33	MPI_0	SPG	MDPI
2004	38.32	94.16	56.16	6.71	30.27	37.25	1.71	18.99
2006	38.98	92.46	54.29	7.10	29.79	36.71	1.78	19.07
2008	48.09	90.78	48.78	9.67	25.66	33.24	2.69	16.11
2010	25.95	90.55	46.45	3.47	24.28	31.99	0.69	15.26
2012	25.17	88.63	42.46	3.70	22.06	30.05	0.81	14.01
2014	13.20	87.84	39.29	1.58	20.28	28.24	0.29	12.91

Notes: see Table D1

Figure E1

Districts showing opposite movement in poverty trends using conventional and non-conventional Distribution-insensitive measures (MPI and PG) for at least 2 spells (out of 5)

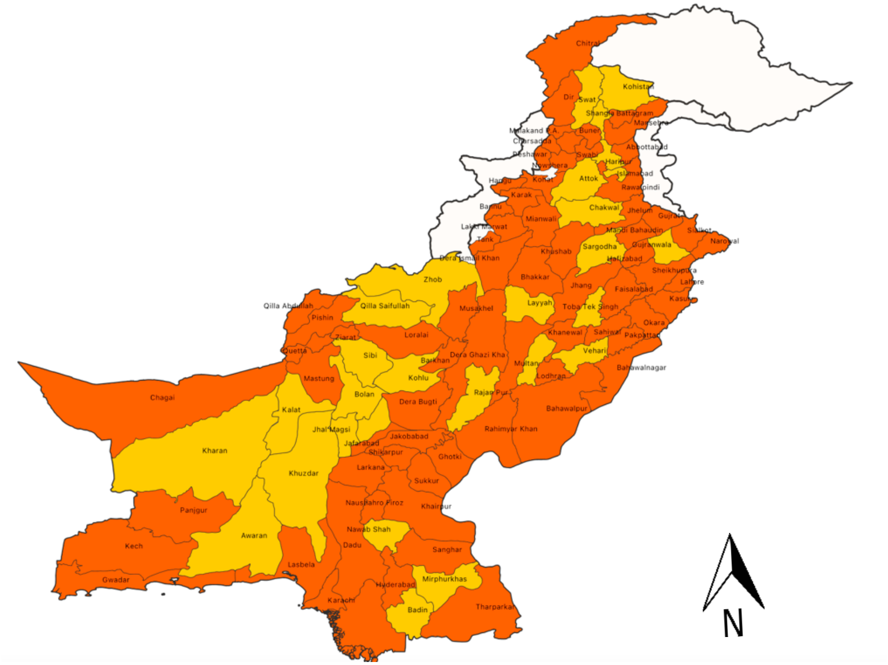
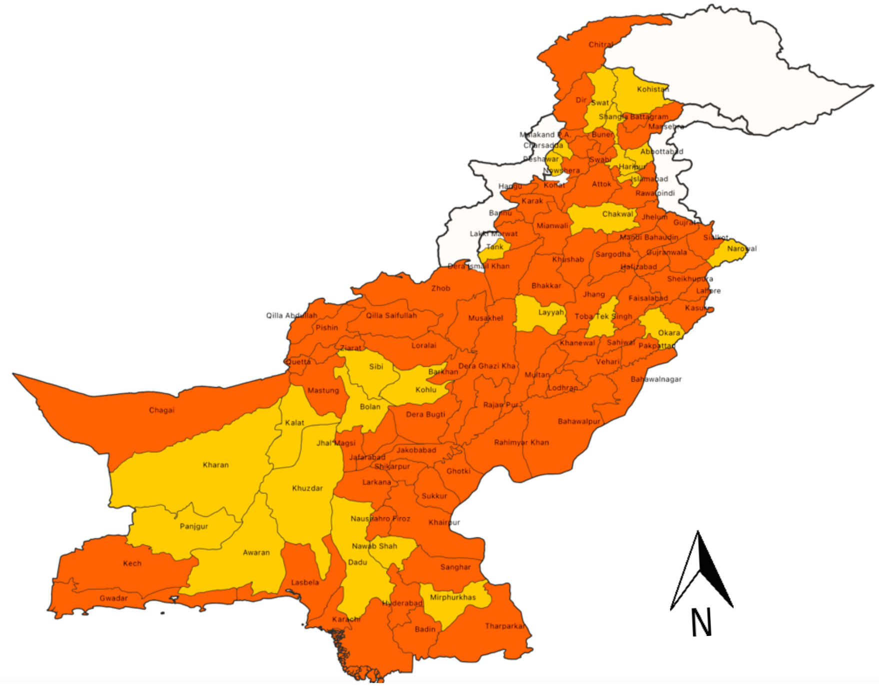


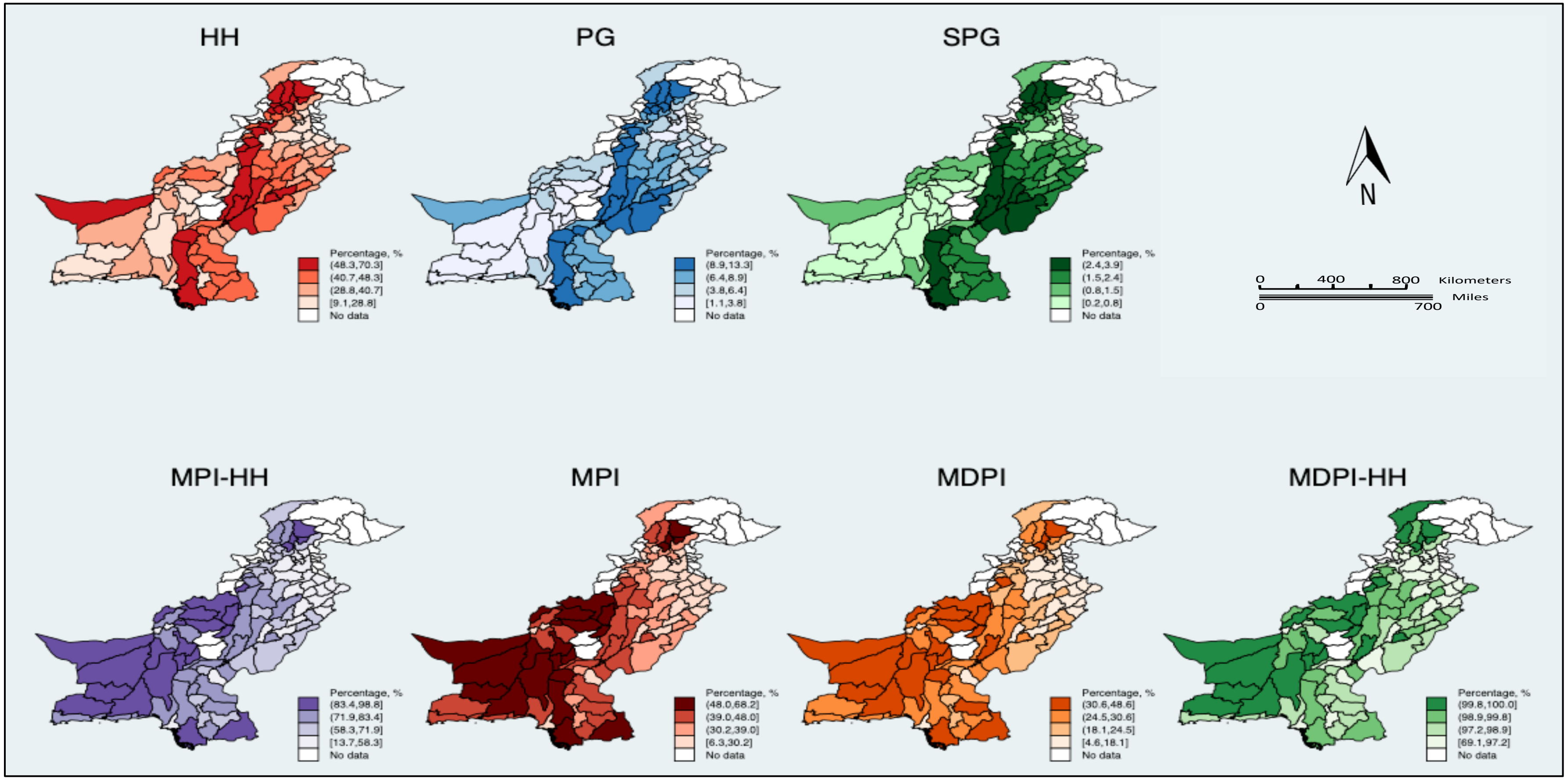
Figure E2

Districts showing opposite movement in poverty trends using conventional and non-conventional Distribution-sensitive measures (MDPI and SPG) for at least 2 spells (out of 5)



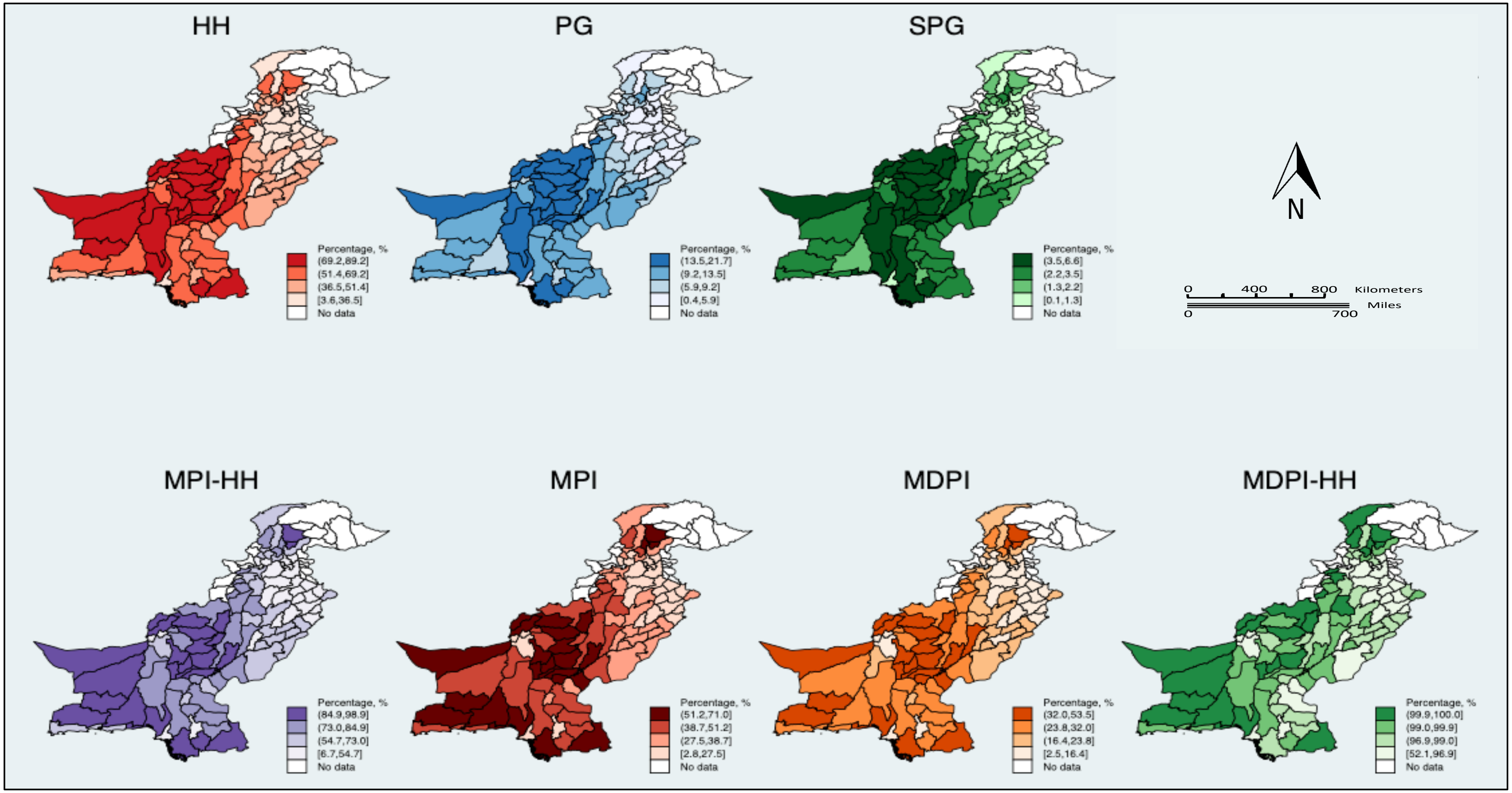
Districts showing opposite movement for >= 2 spells (out of 5)
Districts showing opposite movement for < 2 spells (out of 5)

Figure F1 Poverty mapping for poverty measures (distribution sensitive and insensitive) – 2004



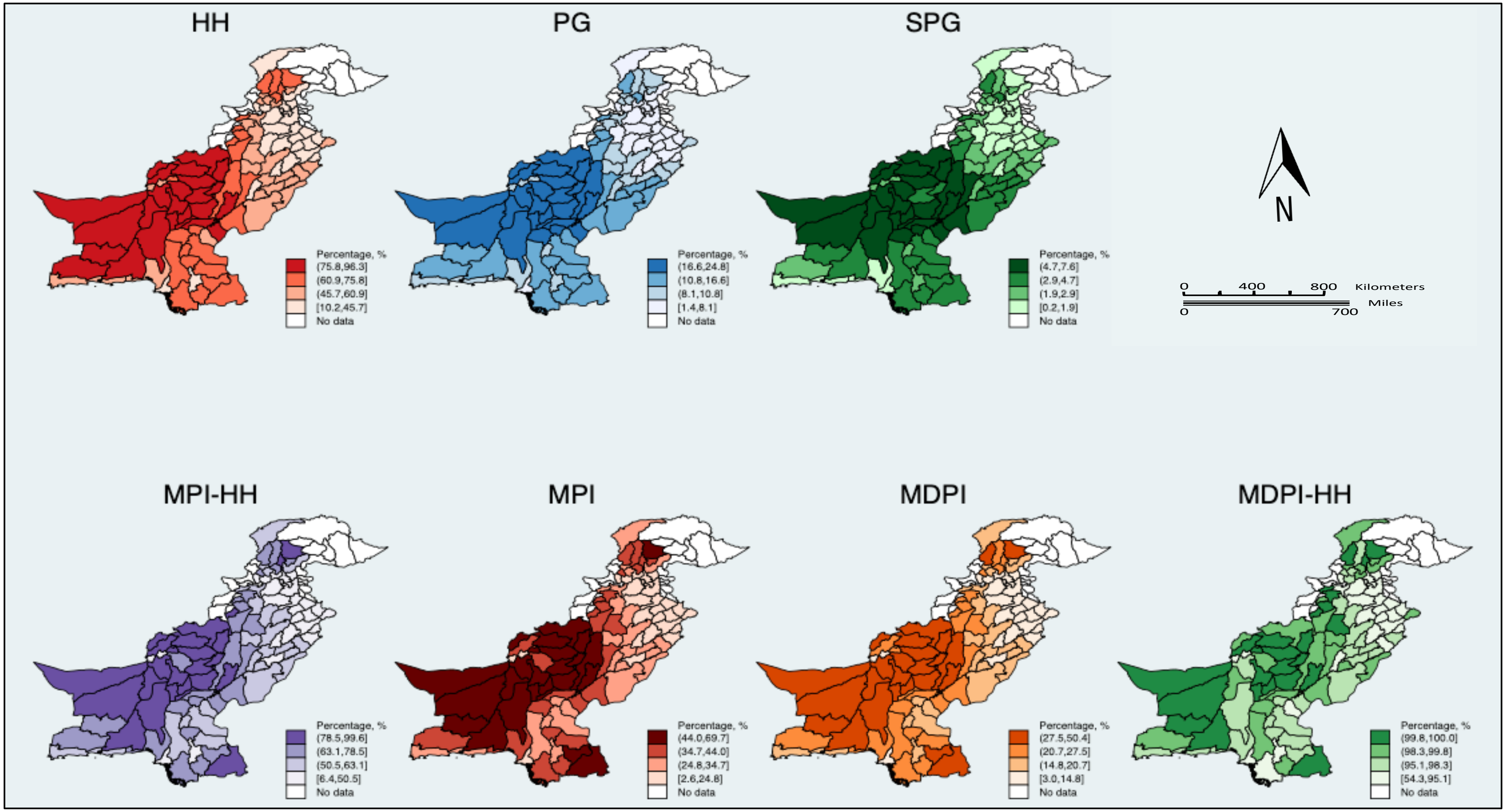
Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

Figure F2: **Poverty mapping for poverty measures (distribution sensitive and insensitive) – 2006**



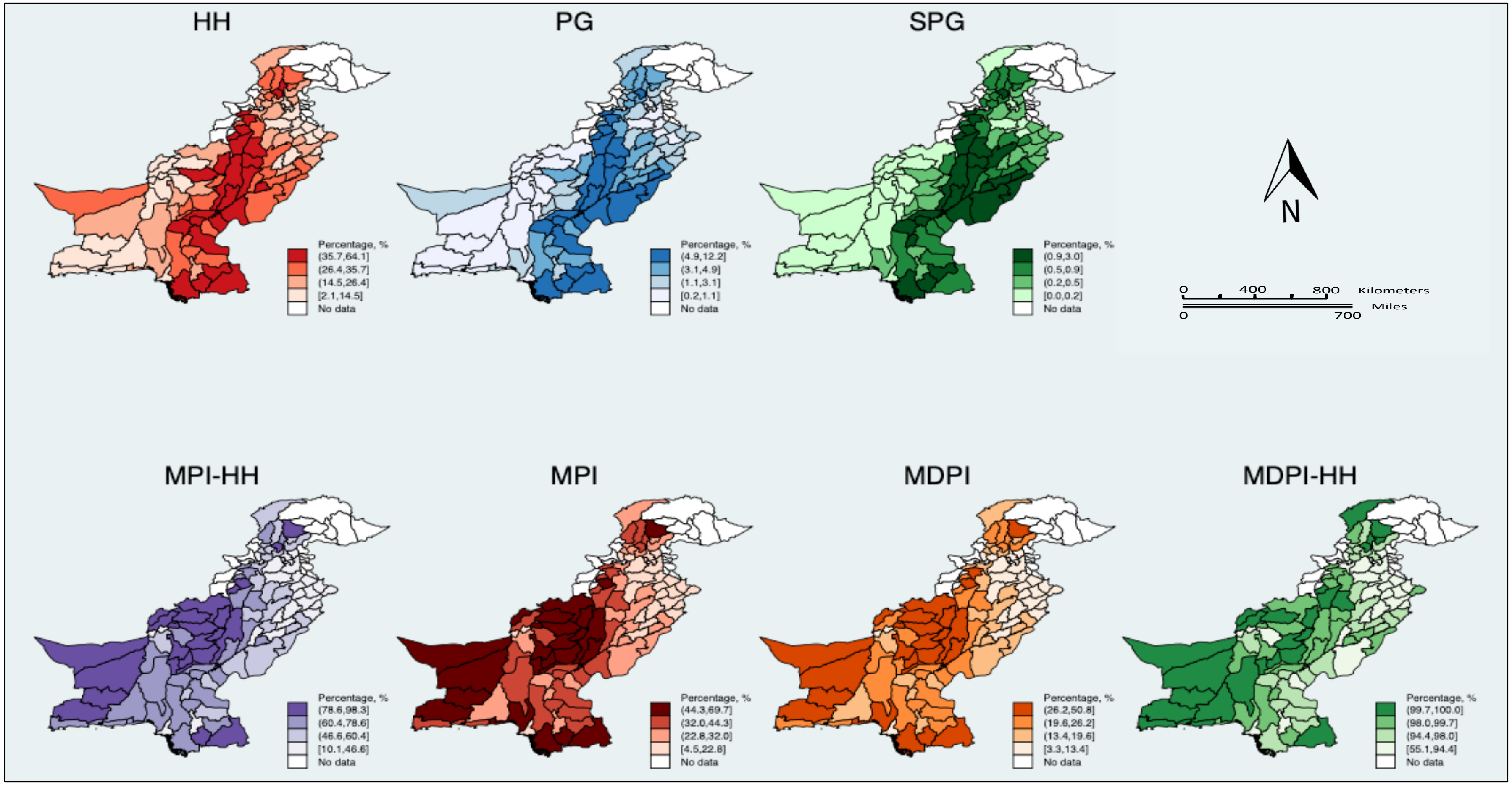
Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

Figure F3: Poverty mapping for poverty measures (distribution sensitive and insensitive) – 2008



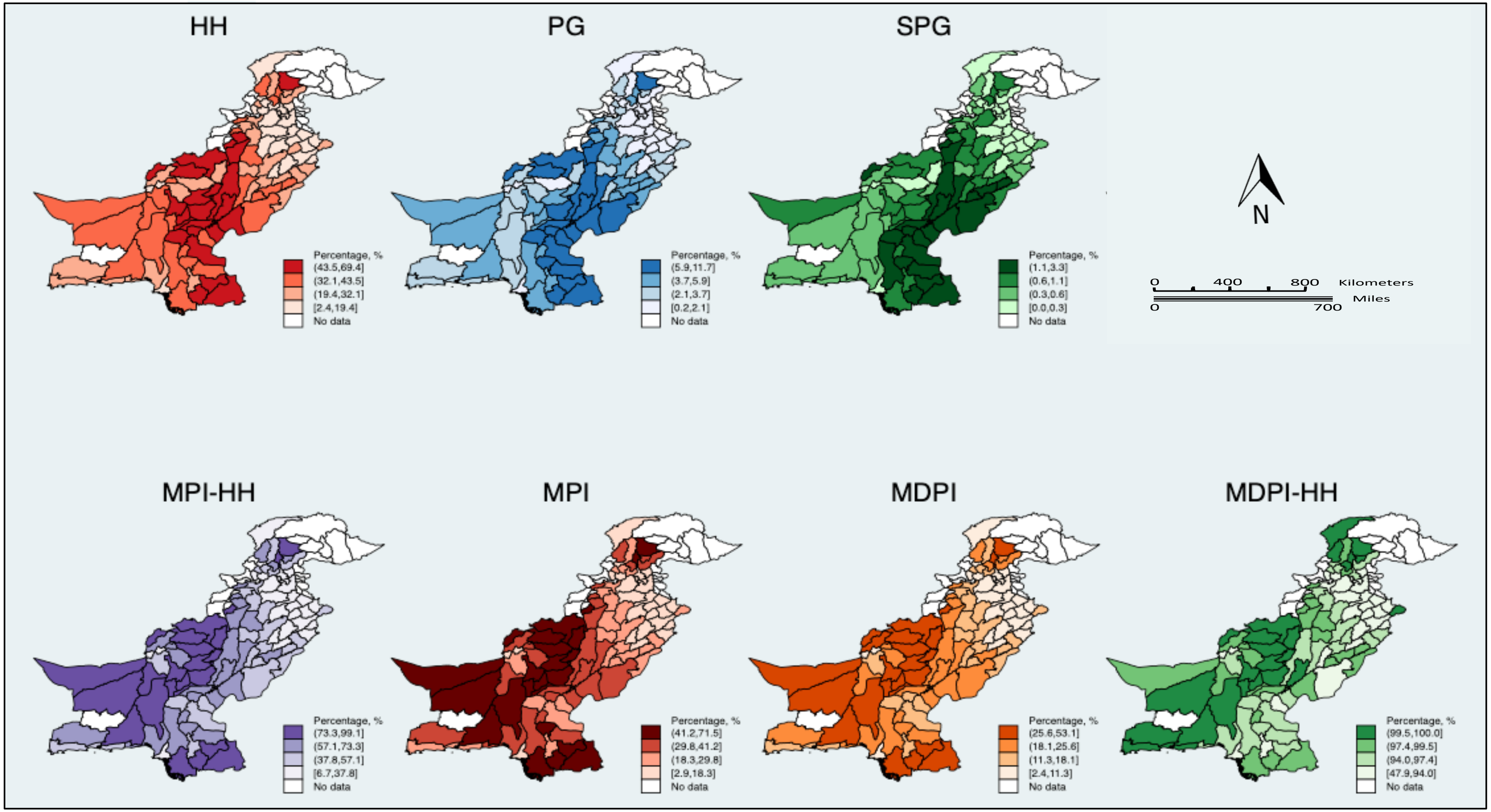
Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

Figure F4: Poverty mapping for poverty measures (distribution sensitive and insensitive) – 2010



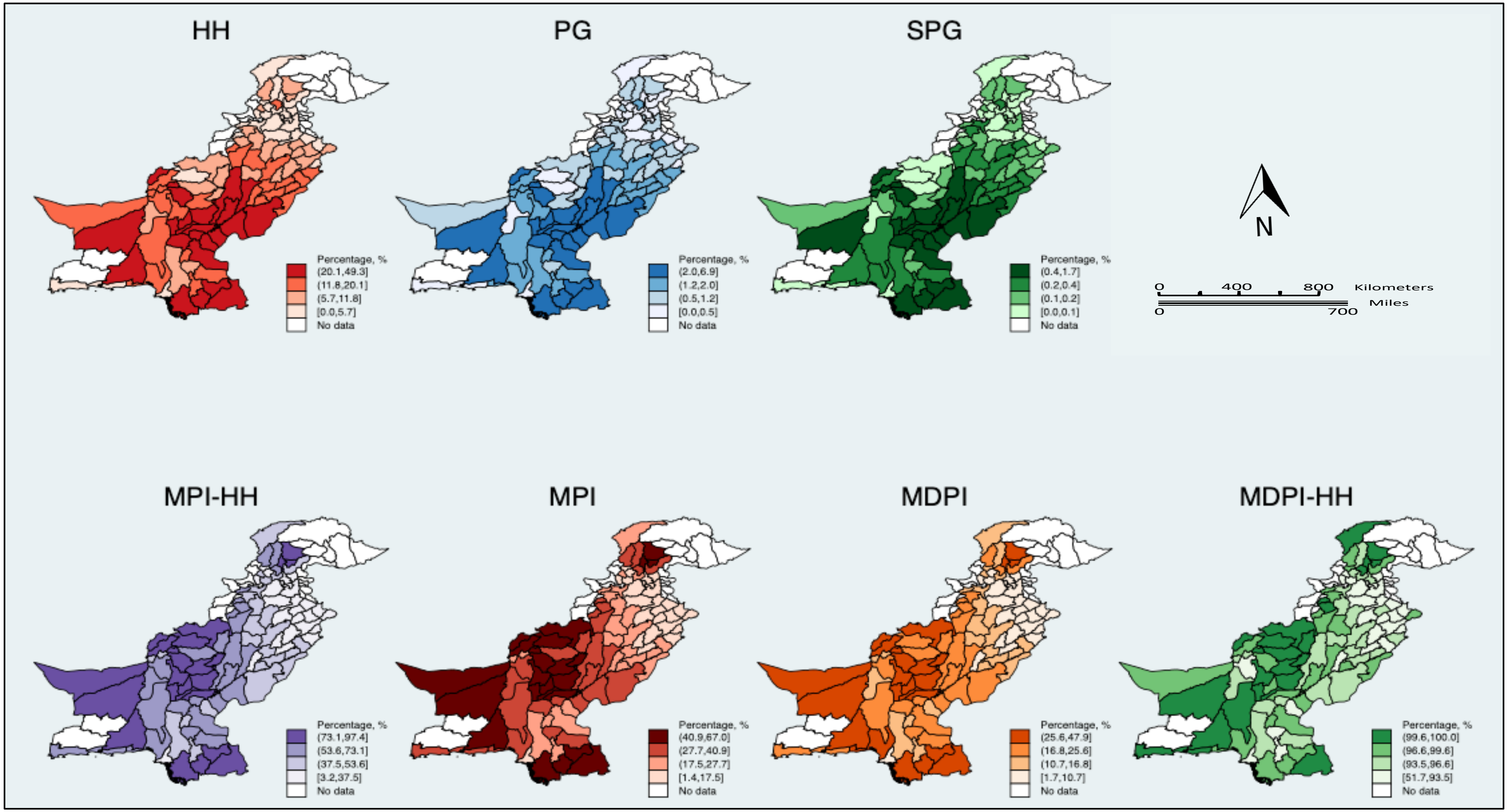
Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

Figure F5: Poverty mapping for poverty measures (distribution sensitive and insensitive) - 2012



Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

Figure F6: Poverty mapping for poverty measures (distribution sensitive and insensitive) - 2014



Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap; MPI, Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index

Appendix G

Table G1: Small Area Estimation Model Results (HIES 2007-08 into PSLM 2006-07)

Statistics	2006	
	Urban	Rural
Error Decomposition	ELL	ELL
Beta Model Diagnostics		
Number of Observations	6250	9247
Adjusted R Squared	0.43	0.40
R Squared	0.43	0.38
Root MSE	0.49	0.36
F Stat	103.1	105.1
Alpha Model Diagnostics		
Number of Observations	6250	9247
Adjusted R Squared	0.012	0.024
R Squared	0.017	0.027
Root MSE	2.346	2.308
F Stat	3.172	8.858
Model Parameters		
Sigma ETA Sq.	0.103	0.024
Ratio of Sigma ETA sq over MSE	0.426	0.189
Variance of Epsilon	0.139	0.103
Sampling Variance of Sigma eta sq	$5x10^{-5}$	$3.3x10^{-6}$

Table G2: Poverty estimates (HIES 2007-08 into PSLM 2006-07) at provincial level

YEAR		HH-05/06	HH-07/08	PG-05/06	PG-07/08	SPG-05/06	SPG-07/08
2006	National	38.32	38.86	6.71	7.02	1.71	1.84
2006	Punjab	33.58	34.13	5.88	6.38	1.45	1.77
2006	Sindh	42.22	42.10	8.43	8.33	2.23	2.24
2006	Khyber Pakhtunkhwa	44.27	41.76	7.01	5.63	1.56	1.13
2006	Balochistan	71.82	70.95	15.43	12.61	4.27	2.87

Notes: 05/06: HIES 2005-06 into PSLM 2006-07; 07/08: HIES 2007-08 into PSLM 2006-07; HH, Headcount Index; PG, Poverty Gap; SPG, Squared Poverty Gap

Appendix H

Table H1: Trends of MPI dimensions (Headcounts)

year	2004	2006	2008	2010	2012	2014
Years of schooling	57	57	54	52	49	48
Child school attendance	27	25	22	21	19	18
Quality of Schooling	23	20	20	18	19	18
Access to health facilities	42	44	43	39	39	32
Immunisation	12	20	15	13	12	14
Ante-natal care	25	22	20	17	14	13
Assisted delivery	26	30	8	13	11	11
Walls	28	27	25	25	21	18
Overcrowding	41	38	36	38	37	38
Electricity	14	13	9	8	7	6
Sanitation	46	41	37	34	29	27
Water	11	11	11	14	11	11
Cooking Fuel	74	71	70	66	63	61
Assets	67	60	53	51	44	39
Land and Livestock	25	23	24	28	30	30

Appendix I

Table I1: MPI Dimensions Pairwise correlations (2004)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Years of schooling	1.000														
(2) Child school attendance	0.344*	1.000													
(3) Quality of Schooling	0.126*	0.251*	1.000												
(4) Access to health facilities	0.112*	0.082*	0.121*	1.000											
(5) Immunisation	0.127*	0.113*	0.050*	0.047*	1.000										
(6) Ante-natal care	0.203*	0.163*	0.061*	0.073*	0.325*	1.000									
(7) Assisted delivery	0.207*	0.166*	0.060*	0.069*	0.305*	0.562*	1.000								
(8) Walls	0.351*	0.261*	0.122*	0.104*	0.089*	0.113*	0.138*	1.000							
(9) Overcrowding	0.157*	0.228*	0.131*	0.040*	0.117*	0.172*	0.172*	0.124*	1.000						
(10) Electricity	0.268*	0.212*	0.154*	0.116*	0.104*	0.094*	0.100*	0.331*	0.058*	1.000					
(11) Sanitation	0.450*	0.289*	0.158*	0.154*	0.117*	0.172*	0.185*	0.482*	0.146*	0.375*	1.000				
(12) Water	0.198*	0.164*	0.119*	0.080*	0.083*	0.091*	0.096*	0.196*	-0.011*	0.283*	0.283*	1.000			
(13) Cooking Fuel	0.384*	0.227*	0.112*	0.165*	0.102*	0.189*	0.209*	0.317*	0.126*	0.215*	0.466*	0.184*	1.000		
(14) Assets	0.427*	0.239*	0.132*	0.117*	0.079*	0.142*	0.153*	0.301*	0.251*	0.245*	0.398*	0.159*	0.384*	1.000	
(15) Land and Livestock	0.115*	0.031*	0.001	0.029*	0.006*	0.023*	0.036*	0.114*	0.080*	0.014*	0.145*	0.020*	0.203*	0.156*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

CHAPTER 5[16]

Does within-country poverty convergence depend on spatial spillovers and the type of poverty measure? Evidence from Pakistan

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[16] This paper has been submitted to Asia and the Pacific Policy Studies

Abstract

Knowing whether poverty rates converge within a country matters for regional development policy and for understanding growth processes. In this paper I use five poverty measures, calculated biennially from 2004 to 2014 for 100 districts in Pakistan, to test for poverty convergence. Spatial autoregressive models are used to capture spatial spillovers. Conventional money-metric poverty measures, such as the headcount index and poverty gap index, show unconditional convergence, and the convergence is more apparent if indirect impacts from spillovers are accounted for. In contrast, two multidimensional poverty indexes show no convergence and no indirect effects coming from spatial spillovers. Catch-up growth in initially poorer areas is apparent with the money-metric poverty measures traditionally used in Pakistan but not with the types of multidimensional poverty measures used officially since 2015. This difference in apparent poverty convergence may affect regional development policy choices.

JEL Codes: I32, R12

Keywords: Convergence, Multidimensional, Poverty, Spatial Spillovers, Pakistan

5.1 Introduction

Living standards widely differ over space in many countries. If poor people are clustered in certain areas, then targeting regional development programs to these areas may be an effective way to alleviate poverty, even if there is insufficient capacity to target individuals or households. Yet unequal treatment of areas may be politically contentious so having firm evidence to underpin regional policy is important. For example, in Pakistan — the setting for the current study — the perception that regional developments spurred by the China-Pakistan Economic Corridor were favouring some areas saw one provincial government take the central government to the court (Shah, 2018). While spatial patterns of poverty matter, regional development policy should also be informed by evidence on changes in poverty over time. If areas with high poverty rates in the past experience slower rates of poverty reduction than other areas, it suggests that the fruits of economic development may not be spreading very widely within a country (Gibson et al, 2005).

In light of these concerns, the question of whether poverty rates converge over time is increasingly studied by economists. A theoretical underpinning for these studies is the Solow-Swan growth model, where falling marginal productivity of capital as more capital accumulates sets an economy on a path towards a steady state (Solow, 1956; Swan, 1956). A key implication of this model is that poor places that are further from their steady state, where capital is less abundant, should have a higher growth rate. In addition to this source of convergence, the so-called *advantage of backwardness* (Gerschenkron, 1962) comes from the possibility of poorer areas adopting technologies developed in richer areas. Poverty rates are lower if mean income is higher, holding inequality constant, so the faster rate of growth for poorer areas implied by convergence should see poverty rates fall fastest in places with higher initial poverty rates.

Yet despite a convergence in average living standards amongst developing countries a seminal paper found no poverty convergence; countries with initially higher poverty rates did not see faster rates of poverty reduction (Ravallion, 2012). This finding spurred other studies, that find poverty convergence between countries if attention is restricted to certain regions such as Sub-Saharan Africa (Ouyang et al, 2019), if attention is paid to convergence clubs (Marrero et al, 2017), or if different functional forms for the relationship between initial levels of poverty and poverty changes are used (Cuaresma et al., 2017). Convergence within a country should be faster than between countries, due to freer movement of capital and labour, and to fiscal transfer systems that supra-national groupings cannot match. Hence, several studies find within-country poverty convergence. For example, by grouping all provinces in Turkey into 26 regions and then looking at the 19 regions outside the largely rural East, Azevedo et al. (2016) find that regions with higher initial poverty rates in 2006 had greater reductions in poverty from 2006 to 2013. More compelling evidence comes from Lopez-Calva et al. (2020), who find convergence when studying poverty changes for 2400 municipalities (the second sub-national level) in Mexico between 1992 and 2014.

Despite these extant studies, there are at least two reasons why the evidence on within-country poverty convergence is insufficient. First, the evidence is for traditional, money-metric poverty measures, such as the *headcount index* (the share of the population living in households whose consumption or income is below the poverty line) and the *poverty gap index* (the average proportionate shortfall from the poverty line). Yet many developing countries are switching to multidimensional poverty measures (Alkire et al., 2015; UNDP, 2016) to either supplement or replace the traditional money-metric ones. While Amaghouss and Ibourk (2020) study poverty convergence (in Morocco) using the Alkire and Foster (2011) Multidimensional Poverty Index (MPI), no studies compare convergence in multidimensional measures versus in money-metric measures.[17] Other aspects of poverty analysis for Pakistan, such as spatial patterns and temporal changes, appear to be sensitive to using multidimensional versus money-metric poverty measures (Najam, 2020) and so it is worth testing whether evidence for poverty convergence also depends on the type of poverty measure used.

The second reason the existing evidence is insufficient is that studies use the traditional econometric assumption that each cross-sectional unit — districts in our setting — is independent of every other unit. In reality, it can be hard to make much progress in reducing poverty in a particular district if it is surrounded by other districts that are doing poorly, while conversely, having neighbours who are doing well can help with more rapid poverty reduction because of the economic linkages between nearby areas. For example, in neighbouring India, the elasticity of own-region poverty with respect to the poverty rate of neighbouring regions is 0.3 and the rate for neighbours always significantly predicts own-region poverty (Gibson et al, 2017).

Given these gaps in the evidence, this paper reports on tests for poverty convergence within Pakistan. Our database consists of 100 districts, observed six times (biennially from 2004 to 2014). I use five different poverty measures; two multidimensional and three money-metric. One measure from each of these groups is distributionally sensitive. With this multitude of measures I can assess whether evidence for convergence, that to date is mostly for money-metric poverty, is sensitive to the type of poverty measure used. To allow for spatial spillovers I use spatial autoregressive models, where poverty changes in nearby districts may affect the

[17] Moreover, the MPI is not distributionally sensitive, and therefore it violates a desirable property (the strong transfer axiom) for a poverty measure (Datt, 2019).

rate of poverty change in the district under consideration. These models recognize the economic inter-connections between nearby districts.

I find that all three money-metric measures show unconditional convergence and the rate of convergence is faster when indirect impacts from other districts are accounted for. In contrast, there is no convergence for either of the two multidimensional poverty measures, irrespective of whether I allow for spatial spillovers or not. There are at least two implications of these results. First, the catch-up growth for initially poorer areas that is apparent with the money-metric poverty measures traditionally used in Pakistan is not seen in multidimensional measures. Thus, an apparent policy failure, of the districts with high initial multidimensional poverty rates not showing much decline in poverty, may just reflect what is being measured, given that there is a decline in poverty and unconditional convergence when the money-metric measures are used. The architects of regional policy should be made aware of this fragility in the evidence, in terms of the dependence on the type of poverty measure used. Second, the evidence for spillovers suggests data requirements for spatial targeting need not be too onerous; even if it is not possible to target individual districts, poverty-alleviation programs for groups of nearby districts may be sufficient, given the inter-district spillovers.

The rest of the paper is set as follows: Section 2 provides details on poverty in Pakistan and description of the data that I use. Section 3 discusses methods of testing for convergence and of testing for, and allowing, spatial spillovers. Section 4 has the results and Section 5 concludes.

5.2 Poverty in Pakistan: Background and Data

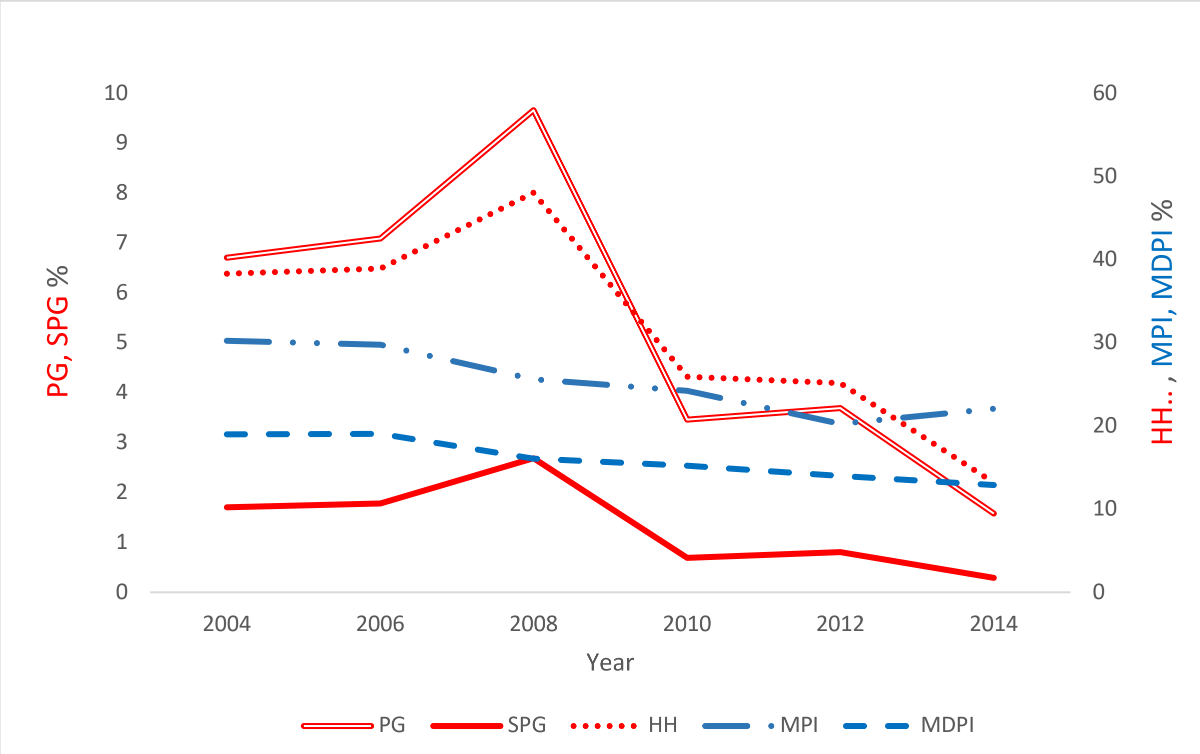
Traditionally the Government of Pakistan (GoP) used money-metric poverty estimates derived from detailed household consumption surveys to target social safety net programmes. This system was put under considerable stress in 2008 when Pakistan's annual inflation rate briefly hit 21% (up from 12% the year before) as world food prices surged. The money-metric measures of poverty showed a sharp increase in 2008 from their previous values in 2006 (the surveys are biennial), especially for poverty depth (the average shortfall from the poverty line). Hence, the GoP then switched from Community Based Targeting to the Benazir Income Support Programme (BISP) that uses Proxy Mean Testing (PMT) to identify poor households. With PMT, money-metric measures based on detailed consumption surveys were no longer needed, as poor households are identified by using indicators such as health and education. These non-monetary measures were further developed into multidimensional poverty estimates, in line with a switch away from relying on money-metric poverty measures in several other countries.

The evolution of average poverty rates over the six waves of surveys that I use from 2004 to 2014 is shown in Figure 1. The three money-metric measures shown in the figure 1 are the headcount index (HH), the poverty gap index (PG) and the squared poverty gap index (SPG). The SPG is a distributionally sensitive measure, that puts more weight on the people furthest below the poverty line, while HH and PG are not distributionally sensitive. The other two measures are the MPI, which is based on Alkire and Foster (2011) and Alkire et al (2015), and the multidimensional distribution-sensitive poverty index (MDPI) developed by Datt (2019). As the name implies, the MDPI is distributionally sensitive while the MPI is not. The detailed formulae for these five indices are provided in Appendix A, with full details on the survey data used to construct them in Najam (2020). For our purposes here, it is sufficient to note that I have estimates at district-level for every second year, from 2004 to 2014.[18] I control for the

[18] For money-metric poverty measures, this involves an Elbers et al (2003) approach to project consumption data from the Household Income and Expenditure Surveys (HIES) onto the sample of the Pakistan Social and Living Standards Measurement Surveys (PSLM) that lacks consumption data, using sets of predictor variables from the two surveys that overlap (see Dang et al, 2019 for a review of these methods). PSLM surveys are representative at district-level, and are used to directly calculate the multidimensional poverty measures. This survey-to-survey imputation approach provides district-level money-metric poverty estimates. Full details are

occasional splitting of districts by using the administrative geography from 2004.

Figure 1: The average poverty estimates (district-level) for six alternative years (2004 – 2014)



The headcount poverty rate was around 40% in 2004 and 2006 but rose to almost 50% in 2008 (see Figure 1). These increases were followed by an even sharper fall, to about 25% in 2010, with a slight decline in 2012 and then a further sharp decline to below 15% by 2014. The movements of the poverty gap index (which uses the left-hand axis, while the headcount index and the multidimensional measures use the right-hand axis) was even more pronounced, rising faster from 2006 to 2008 and then declining even faster than what the movements in HH show. The patterns for SPG are similar but with less sharp movements, so the overall patterns revealed by the money-metric measures is that poverty rates in 2014 were substantially lower than in

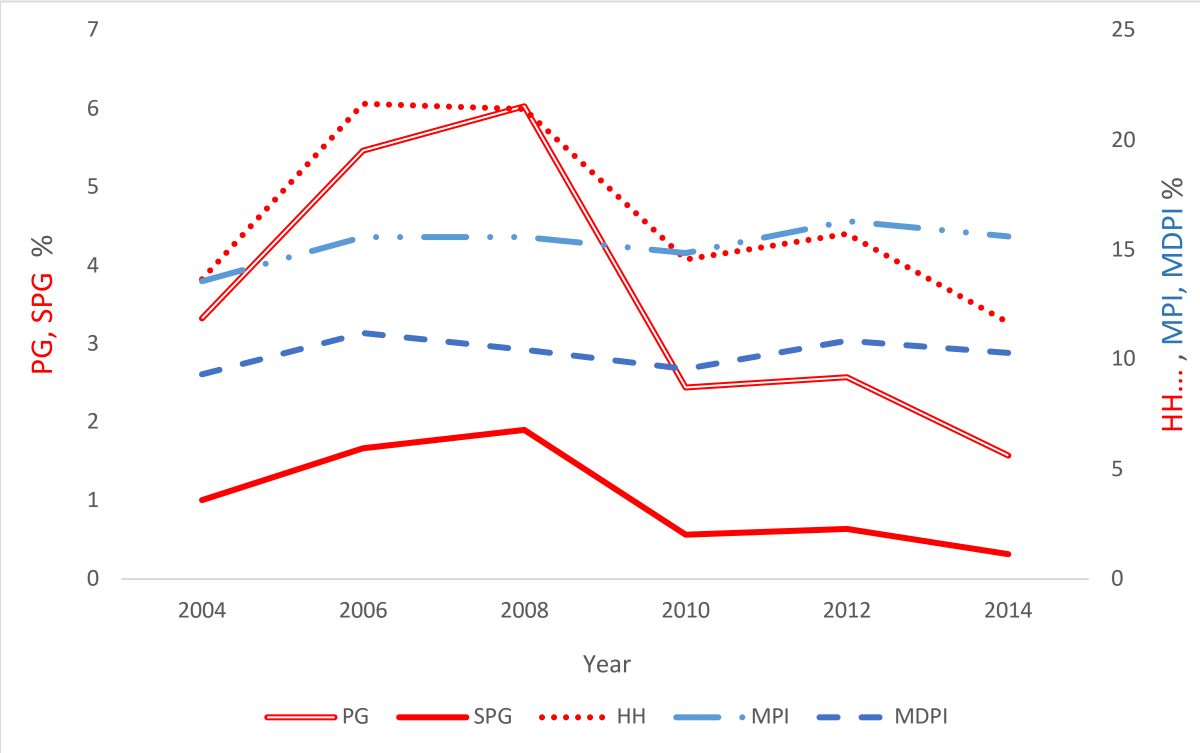
available in Najam (2020). This approach to generating spatially disaggregated poverty estimates is also used in the convergence study of Azevedo et al (2016).

2004, albeit with an initial period of rising poverty, especially in 2008.

The multidimensional poverty measures present quite a different picture. There was a slow decline in the MPI, with an average index value of about 30% in 2004 declining to be just above 20% by 2014. The average level of the MDPI starts lower but does not decline quite as fast and neither measure shows any jump in 2008, unlike the fluctuations seen with the money-metric measures. The trends shown in Figure 1 relate to averages over all 100 districts (and years) but a disaggregated analysis by Najam (2020) also shows that the time trends in poverty in Pakistan depend on what sort of measures are used; over two-thirds of the districts show opposite trends in poverty rates, if using multidimensional measures rather than money-metric ones, for at least two of the five spells between the six survey waves.

Another way to show how the differences across districts in their poverty rates evolved is to chart the movements in the standard deviation of the district-level poverty rates. All five poverty measures show increases in the standard deviation of the poverty rates between 2004 and 2006, so there was an initial tendency for the districts to become more dissimilar in their poverty rates (see Figure 2). This increased inter-district variance was observed also in 2008 for PG and SPG but the other three poverty measures showed slight falls in the variance that year. There were sharp falls in the standard deviations for money-metric poverty measures in 2010 that slightly reversed in 2012 and then fell further in 2014. In contrast, the standard deviation of the multidimensional measures was largely unchanged after 2010. Overall, the districts have become more alike in their money-metric poverty rates over time, but the multidimensional measures show that the inter-district differences in multidimensional poverty rates have not changed much across the six surveys that I examine.[19]

Figure 2: The standard deviations of districts' poverty estimate for six alternative years (2004 2014)

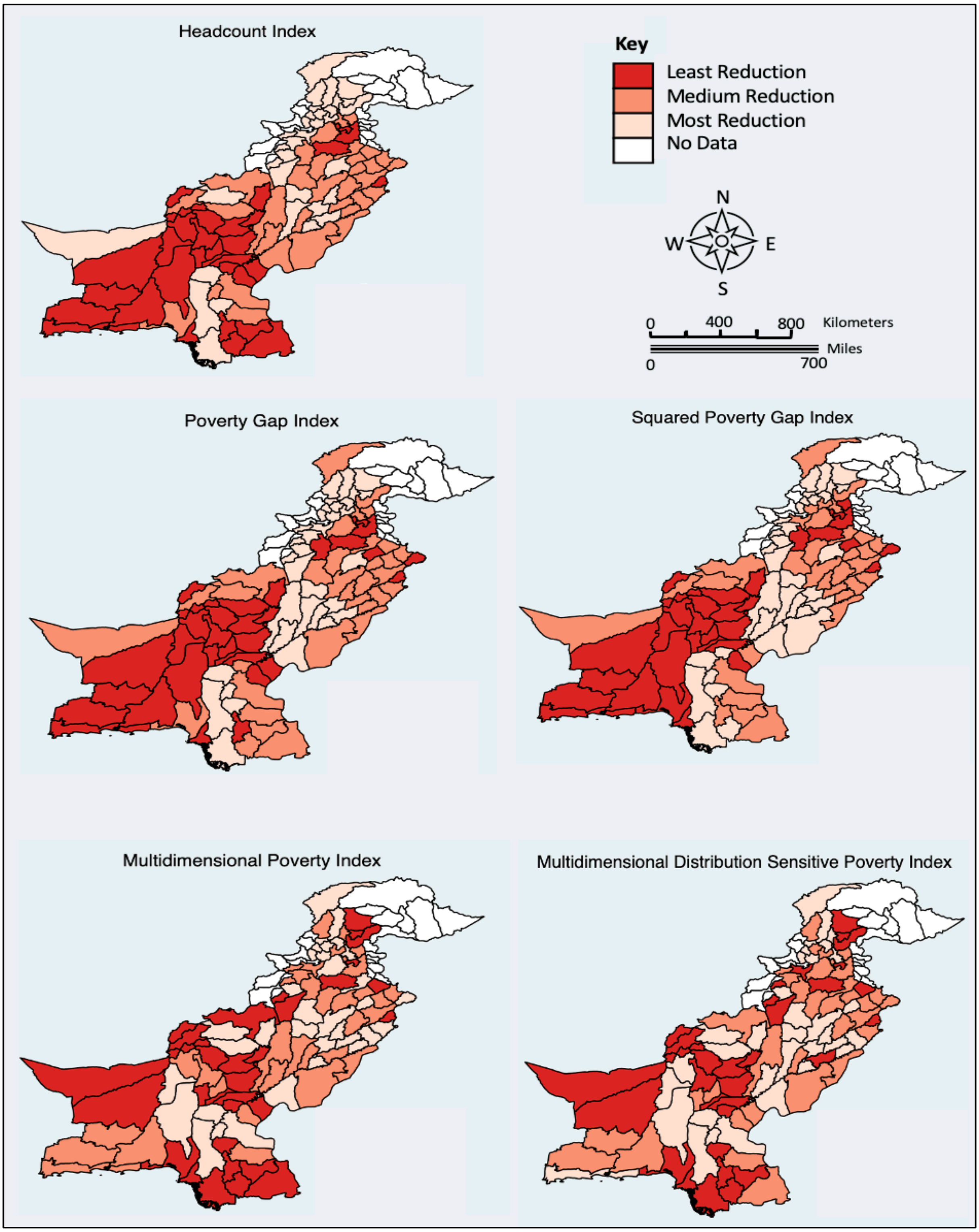


The last pattern I examine before discussing the methods of testing for convergence is the question of where in Pakistan have the declines in poverty rates been most apparent. In Figure 3, I present district-level maps of the change in the poverty rates over the 2004 to 2014 period for the five poverty measures that are our focus. For clarity of presentation, I group districts into terciles, in terms of those that saw the smallest rate of poverty reduction, those with medium rates of poverty reduction, and those with the fastest rates of poverty reduction (so the thresholds for inclusion in these groups differs between the poverty measures). The darker colours on the map denote districts that had the slowest rates of poverty reduction. There are

[19] The evidence in Figures 1 and 2 weights districts by their population, but similar time patterns would show up if unweighted averages and standard deviations were shown.

also some districts with no data, mainly in the Federally Administered Tribal Areas (FATA), where the PSLM surveys were not fielded due to the security situation.

Figure 3: Spatial depiction of the change in poverty estimates for the districts between 2004 - 2014



A group of neighbouring districts in Balochistan province (in the southwest) are amongst those with the least reduction in money-metric poverty measures over 2004-2014 (see Figure 3). The larger physical size of some of these districts draws attention to them but it is also the case that the majority of districts in the tercile with the least poverty reduction are in Balochistan. This spatial clustering of districts that were less successful in achieving poverty reduction implies that spillovers may be important in the Pakistan context. Indeed, a Moran *I* statistic strongly rejects the null hypothesis of spatial randomness (with a χ^2 statistic of 65.4 which is statistically significant at $p<0.01$) in the pattern of changes in the headcount index.

In contrast to the maps for money-metric poverty measures, where the tercile with the slowest rates of poverty reduction is mostly in Balochistan and a few scattered parts of northern Punjab, the multidimensional poverty measures show patterns that are more spatially random. The tercile with the slowest rates of reduction in multidimensional poverty includes parts of Sindh and Khyber Pakhtunkhwa provinces, plus districts from Balochistan and Punjab. With this scatter, it is unsurprising that the Moran *I* statistic for changes in either multidimensional poverty measure less strongly rejects spatial randomness, with χ^2 values of just 3.6 and 3.3. This closer to random pattern, for changes in the multidimensional poverty measures, suggests that any spillovers may be less important for them than for the money-metric poverty measures.

5.3 Methods of Testing for Convergence and Spatial Spillovers

The regression model for the test of unconditional convergence, adapted to our setting, is:

$$\Delta PI_{it=0-it=1} = \alpha + \beta(PI_{it=0}) + \varepsilon_i \qquad (1)$$

where ΔPI is the annualised change in the poverty rate (for a particular poverty measure like HH or MPI) for district i from T_0 = 2004 to T_1= 2014. This is simply the change in the poverty index (P_1 –P_0) from time T_0 to T_1 averaged over time T ($T = T_o – T_1$). This outcome variable is regressed on the initial poverty rate: $PI_{it=0}$ in our case is for the year 2004 for the i^{th} district. Unconditional convergence holds when β is statistically significant with a negative sign. In that case, the districts with a higher initial rate of poverty have larger changes (falls) in poverty. Some prior studies use percentage rates of change (e.g. Ravallion, 2012) while a majority use the absolute change (e.g. Azevedo et al, 2017; Cuaresma et al, 2017; Marrero et al, 2017; Lopez et al, 2020) when calculating the time-averaged rate of change. I follow the approach that is used in the majority of studies.

The regression error, ε_i from equation (1) is typically treated as independent of errors for the other cross-sectional observations (that is, for $i \neq j$). Yet the maps shown in Figure 3, and the Moran *I* statistics for spatial randomness, suggest that there is cross-sectional dependency where the change in poverty for one district is related to the change in poverty for the nearby districts. This lack of independence in the outcome variable is likely to transmit through into the regression errors, and so the traditional testing approach that assumes independence for ε_i may be mis-specified. Also, the right-hand side variable in equation (1) may exhibit dependence on poverty rates of the nearby districts; the baseline poverty rates (in 2004) also showed some spatial clustering, where poor districts were near to other poor districts and richer districts were near other richer districts.

A more general model than equation (1), that lets the change in poverty and the initial level of poverty in a district influence poverty changes of nearby districts, is a spatial regression model. The key aspect of this model is that spillovers can be allowed for with a spatial weights matrix, W. Several types of weights matrix can be used, ranging from a simple 0/1 matrix where a district is defined as a neighbour (typically based on contiguity) or not, through to more complex distance-based matrices where closer districts have more influence and further away ones have less influence (LeSage and Pace, 2009). I use Euclidean distance to form a weights matrix, as this allows for the variation in population density in Pakistan. Specifically, I find the geographic centroid of each district in Pakistan and then the inverse of the distance from that centroid to the centroid of any other district is the weight I put on the observations from the other districts. These weights let us form spatial lags; the weighted averages over the other districts of the dependent variable, of the independent variable(s) and (potentially) of the errors. These lags allow estimation of a more general model:

$$\Delta PI_{it=0-it=1} = \alpha + \beta PI_{t=0} + \delta W \Delta PI_{it=o-it=1} + \lambda WPI_{it=0} + \mu_i \tag{2a}$$

$$\mu_i = \gamma W \nu_i + \varepsilon_i \tag{2b}$$

There are three additions in equation (2a) compared to equation (1). The $W\Delta PI$ term is the weighted average of the change in poverty rates in all 100 districts, with higher weights on nearby districts. If the δ coefficient is statistically significantly different from zero it implies the presence of global spillovers, where the change in poverty in one district will propagate through all the districts (including feedback effects to the district under consideration). The $WPI_{it=0}$ term is the weighted average of the initial poverty rates; if the λ coefficient on this term is statistically significant it implies local spillovers, where a higher or lower initial poverty rate of a neighbour affects poverty changes in a district, without the effect spreading globally through all 100 districts. The third addition is that the error term now has a potential correlation, shown by the γ coefficient, with the error terms for nearby districts. This spatial autocorrelation may affect inferences if information in the spatial pattern of the regression errors is ignored.

The model set out in equations (2a) and (2b) is a very general one that nests several other commonly used models. If $\gamma = 0$ the resulting model is a spatial Durbin model that has lags of the outcome variable and of the right-hand side variable. The spatial auto-regressive model (*aka* the spatial lag model) results if $\lambda = \gamma = 0$, where only the dependent variable is spatially lagged. A spatial error model results if just errors are spatially lagged (so $\lambda = \delta = 0$). An ordinary least squares model without any spatial lags results if: $\lambda = \delta = \gamma = 0$. Neither the spatial error model nor the OLS model generate any spillovers where shocks to the right-hand side variable in one location may propagate through other observations and cause a total impact that may exceed the initial direct impact given by the $\hat{\beta}$ coefficient. The general nesting model is known as a spatial autoregressive model with autoregressive errors (SARAR), and using it as a starting point should give unbiased coefficient estimates even if the true data-generation process is one of the nested models.[20] Notably, the reverse is not true given that estimating one of the nested models if the true model is SARAR involves omitting relevant variables.

With either local or global spillovers, the changes in a right-hand side variable—in this case a different initial poverty rate—will produce both direct and indirect effects. The indirect ones are not just from nearby districts if $\lambda \neq 0$, but also from (potentially) all areas through the spatial autoregressive effect when $\delta \neq 0$. Specifically, a local change in the initial poverty rate may affect how quickly poverty declines in the own-district and also in nearby districts. This spillover to nearby districts may, in turn, affect the change in poverty of their neighbours, including the original district. In order to allow for these spillover and feedback effects, I use an estimator with (separately for each poverty measure) a 100×100 matrix of cross-partial effects (given our sample has 100 districts). Each cell in this matrix shows the relationship between poverty in district i and the change in poverty in the j^{th} district. The average direct effect is the effect of a change in a right-side variable *in district i* on the outcome variable in

[20] The SARAR model is estimated using a recently implemented procedure in *Stata* (Drukker et al, 2013). Given that any particular district is it's neighbours' neighbour, there is simultaneity that must be accounted for when estimating equation (2a), which is dealt with by spatial two-stage least squares (Kelejian and Prucha, 1998).

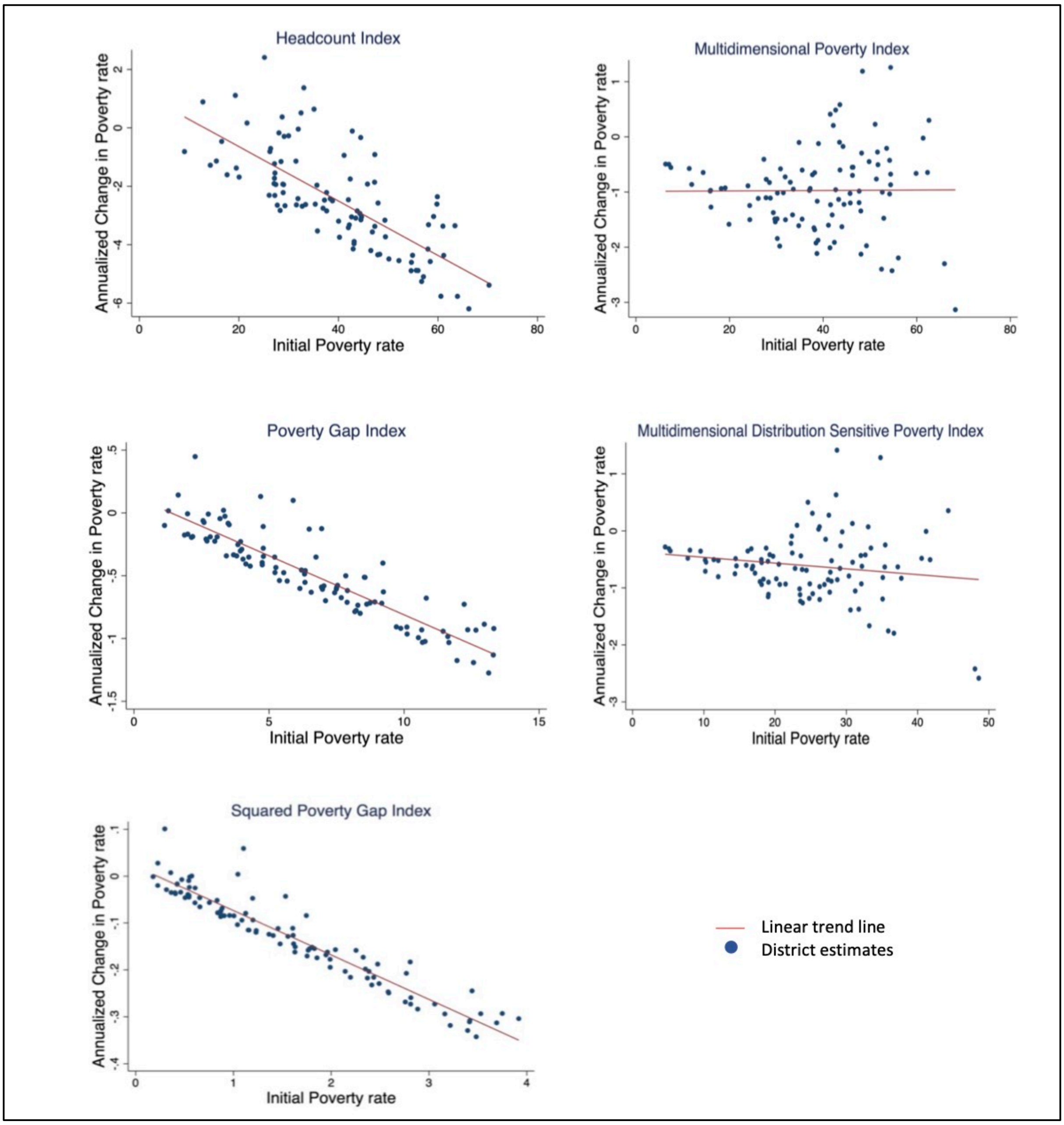
district *i* averaged over all districts (in other words, this average effect is based on cells along the diagonal of the matrix). The total effect is the effect of the same change in the right-hand side variable *in all districts* on the outcome variable in district *i* averaged over all districts. The indirect effect is the difference between the total effect and the direct effect (and is based on the row-sums of the off-diagonal elements of the matrix). This decomposition, which is due to LeSage and Pace (2009), is also used to study poverty spillovers in India (Gibson et al, 2017).

5.4 Results

I begin by presenting scatterplots of the annualized change in the poverty rate against the initial poverty rate, for each of the five poverty measures (see Figure 4). There is a clear negative relationship for the three money-metric poverty measures: the higher the initial poverty rate (in 2004) in a district, the greater the annual average reduction in the poverty rate in that district over the following 10 years through to 2014. The spread of the points around the linear trend line falls when moving from HH to PG to SPG, that is, as attention switches from the simple indicator of poor/not-poor, to also considering how poor (the depth of poverty shown with the PG index), and then further considering differences amongst the poor by putting more weight on those furthest below the poverty line (the severity of poverty shown with the SPG index) the evidence in favour of the unconditional convergence in poverty rates seems to get stronger.

In contrast to the situation with money-metric poverty measures, there is no apparent convergence in the two multidimensional poverty measures. Rather than a downward sloping relationship the scatter of points seems to be more of a fan-shape as moving from a lower to a higher initial poverty rate sees the gap between the lowest and highest districts — in terms of their annualized change in the poverty rate — get bigger. Thus, the districts that had the highest initial values of the multidimensional poverty indexes might have some of the largest annual average falls in the poverty index, or some of the largest annual average rises. Consequently, the trend line is either completely flat, for the MPI, or only slightly downward sloping for the MDPI, compared with the much more steeply downward sloping trend lines for the money-metric poverty measures.

Figure 4: Scatterplots for districts' initial poverty rates and annualized change in poverty estimates between 2004 - 2014



The scatterplots shown in Figure 4 provide a visual counterpart to equation (1), which is the basic equation for testing for unconditional convergence. The regression results that correspond to the linear trend lines in Figure 4 are reported in Table 1. I note that these OLS regressions are special cases of the more general SARAR model, but I present the OLS results before turning to the results from either the SARAR models or the models nested within them because the OLS results link to the scatterplots and also because of the widespread intuition that exists around OLS results (as lines of best fit). The table includes the convergence coefficients, $\hat{\beta}$, which are the slopes of the trend lines in Figure 4.

Table 1: OLS Estimation Results for Equation (1), to test for Unconditional Convergence

	Money-metric			Multidimensional	
Poverty Measures	HH	PG	SPG	MPI	MDPI
Convergence, β	-0.092***	-0.098***	-0.100***	-0.0004	-0.010
	(0.009)	(0.006)	(0.005)	(0.006)	(0.008)
R^2	0.5398	0.8018	0.9045	0.0001	0.0251

Notes: The dependent variable is the annualized change in the poverty rate (estimated separately for each of the five poverty measures), and the independent variable is the initial poverty rate. *N*=100 districts. Standard errors in ( ), with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

For all three of the money-metric poverty measures, a one-point higher initial poverty rate leads to a subsequent annualized rate of change in the poverty rate that is between -0.09 and -0.10. An example may help with the interpretation of these coefficients. Consider a district where the initial headcount poverty rate was ten percentage points higher than in another district; the district with the higher initial poverty rate would have experienced, on average over 2004-14, an annual decline in the headcount poverty rate that was 0.9 percentage points greater than the decline in poverty experienced in the initially lower poverty rate district. These coefficients of unconditional convergence are all statistically significant at the $p<0.01$ level. In keeping with the tighter spread around the trend line in Figure 4, when moving from HH to PG to SPG, the R-squared values for the regressions rise, from 0.54 for HH to 0.80 for PG and to 0.90 for the regression for the SPG poverty measure.

In contrast to the clear evidence of unconditional convergence for the money-metric poverty measures, neither of the two multidimensional poverty measures show any relationship between the initial level of poverty and the average change in poverty. For these measures I cannot rule out the hypothesis that there is zero effect of the initial poverty rate on the change in poverty, and so there is no evidence for unconditional convergence in multidimensional poverty measures for Pakistan.

As noted above, the results in Table 1 are from a model that is a special case of the more general SARAR model that allows spatial lags of the dependent variable, the independent variable, and the errors. In Table 2, I report the results of a general-to-specific model selection approach, where I started with the SARAR model and then removed spatial lags that were statistically insignificant. For the model with the MPI poverty measure, all three spatial lags were statistically significant, while for the MDPI measure, the lags of the error term were not significant, so the resulting model was a Spatial Durbin model with lags of the outcome and of the independent variables. For the three money-metric poverty measures (HH, PG, and SPG) the lags of the independent variable were not statistically significant, so the resulting model was a spatial autoregressive model, with spatially autoregressive errors. A common feature of the selected models for all five poverty measures is that the spatial lag of the outcome measure, has a coefficient, δ, that is always statistically significant. Consequently, there will be global spillovers, where a change in the poverty rate in one district will affect the change in the poverty rates of nearby districts (these autoregressive coefficients range from 0.01 to 0.07), and the change in poverty rates of those nearby districts will, in turn, affect the changes in poverty rates of other areas (including the original district).

Table 2: GS2SLS Estimation Results for Poverty Measures at District-level of Pakistan

		Money-metric			Multidimensional	
Poverty Measures		HH	PG	SPG	MPI	MDPI
Convergence[a] β		-0.075*** (0.007)	-0.084*** (0.004)	-0.089*** (0.003)	-0.017** (0.007)	-0.027*** (0.008)
Spatial Lags	Change in Poverty, δ	0.021*** (0.003)	0.012*** (0.004)	0.007** (0.004)	0.051*** (0.011)	0.065*** (0.019)
	Initial Poverty, λ	-	-	-	0.002*** (0.0006)	0.002** (0.0006)
	Error, γ	0.067*** (0.023)	0.044*** (0.007)	0.043*** (0.007)	0.411*** (0.058)	-
Impacts	Direct	-0.077*** (0.007)	-0.085*** (0.004)	-0.098*** (0.003)	-0.016*** (0.522)	-0.027*** (0.007)
	Indirect	-0.196* (0.121)	-0.060* (0.033)	-0.030 (0.020)	-0.027 (0.031)	0.005 (0.017)
	Total	-0.273** (0.122)	-0.144*** (0.032)	-0.119*** (0.019)	-0.043 (0.026)	0.022 (0.138)
Pseudo R^2		0.6680	0.8438	0.9179	0.0627	0.0549
Wald (spatial lags)	Chi square	49.18***	77.81***	55.47***	76.74***	12.20***
Spatial Correlation	Moran's I	0.012***	-0.002***	-0.008***	-0.008***	-0.011***

Notes: The dependent variable is the annualized change in the poverty rate (estimated separately for each of the five poverty measures). Independent variables are the initial poverty rate and the spatial lags of the dependent and independent variables and the errors. The general to specific selection criteria is used for the model specification. The Wald test is reported for the final model, after dropping insignificant spatial lags. The results are estimated using Generalised Spatial 2 Stage Least Squares (GS2SLS) estimation. N=100 districts. Standard errors in ( ), with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.
[a] With spatial regression models, the total impact, that accounts for direct and indirect effects, provides a more complete account of the convergence effect than what is shown by the direct impact estimate, β.

Given the importance of the spatial lag of the dependent variable, the counterpart to the β coefficient reported in Table 1 is no longer a sufficient measure of convergence. Instead, I focus on the total impacts, which have direct and indirect components, that account for the spillovers. For the money-metric poverty measures, the total impacts are larger than the direct impacts, especially for the headcount index, and are larger than Table 1 results that ruled out any possible spillovers. In other words, there is firmer evidence for convergence in money-metric poverty in Pakistan once spillovers from nearby districts are taken into account. Thus, the poverty reduction in a district will influence poverty reduction in nearby districts, which reflects the spatial clustering seen in Figure 3.

For the multidimensional poverty measures, even though there are significant spatial lags for the dependent variable and the independent variable, total impacts remain statistically insignificant. Thus, even allowing for spillovers, there is no evidence of convergence in the multidimensional poverty measures for Pakistan. This implies that the districts surrounded by districts with high initial poverty rates (calculated through multidimensional indicators) are failing to converge, as their rate of poverty reduction was relatively low.

5.5 Discussion and Conclusions

The question of whether sub-national poverty rates converge matters for the design of regional development policy. In Pakistan, regional development polices have been politically criticised for their apparent biases in favour of some regions and cities. It is therefore important to have an evidence base to underpin these policies. The research reported in this paper attempts to contribute to that evidence base, by examining patterns of poverty changes in Pakistan over the 2004 to 2014 period. I find that districts that started off with higher rates of poverty in 2004 experienced larger reductions in poverty over the subsequent decade, if I use the traditional money-metric poverty measures. In contrast to this pattern, the recently introduced and now widely used multidimensional poverty measures do not exhibit convergence. These results concur with a finding of Najam (2020), that some inferences about poverty changes in Pakistan depend on whether newer multidimensional or older money-metric measures are used.

In addition to this finding about convergence in money-metric poverty but not in the multidimensional poverty measures, another key finding from our study is that the change in poverty in one location is affected by the change in poverty in nearby districts. These spillovers are sufficiently strong that for the headcount index and the poverty gap index, indirect effects coming from other districts (as distinct from the direct effects for the own-district) significantly amplify the convergence pattern. However, multidimensional poverty measures do not exhibit significant indirect effects, and so the pattern of non-convergence in these poverty measures still holds when the more general spatial regression models are used instead of OLS regression. These spatial spillovers in the money-metric poverty measures also imply that even if the authorities in Pakistan lack capacity to target individual districts (due to either insufficient information or to political factors), poverty alleviation interventions targeted at groups of nearby districts may be sufficient, given the inter-district spillovers in money-metric poverty.

The profound difference in results if using money-metric poverty measures instead of multidimensional measures requires some explanation. One factor is a differing role for private sector goods and services compared to government-provided services. The multidimensional measures are based on access to services such as health and education, and also depend on local infrastructure, and these are largely within the domain of government. It has been noted before that public sector development initiatives in Pakistan may be concentrated on specific districts (Sandilah & Yasin, 2011). Relatedly, Mohammad et al (2017) highlight various disparities in infrastructure development between the provinces; for the road network, over two-fifths is concentrated in Punjab, almost one-third is in Sindh, while just 16% is in Khyber Pakhtunkhwa and 11% in Balochistan. To put things in perspective, Balochistan has the largest area of any province and the highest incidence of poverty. To the extent that access to health, education and infrastructure is mediated by either political factors or state capacity, there may be no mechanism with an inherent propensity for worse-served areas to converge with other areas.

In contrast, money-metric poverty is largely determined by household consumption, which is heavily influenced by private sector activity such as own-account agriculture, wage earning, entrepreneurial earnings and so forth. Labour intensive firms might locate in poorer areas because of low wages. Also, either wage income or remittances might provide a possibility for catch-up growth. Moreover, a rise in income and consumption in one district can have ripple effects through supply and demand channels. For example, if incomes in a district rises due to increased economic activity, people there will demand more goods and services and this should also generate demand for goods, services and labour from nearby districts. This is the phenomenon studied by Gibson et al (2017) for neighbouring India, where poverty in rural areas fell by more where and when there was stronger growth in nearby towns and cities. Our results for Pakistan suggest that these spillovers may also occur between districts without big cities. However, these effect may be less likely for infrastructure development and access to public facilitates because the spread of those things is managed externally by the government.

Beyond Pakistan, it would be useful for future research to examine whether evidence of within-country poverty convergence varies with whether money-metric or multidimensional poverty measures are used. As more countries switch to using the multidimensional measures, finding which patterns change, due to a switch in what is measured rather than in what actually changes on the ground, will be important for enhancing our understanding of poverty and of progress towards meeting the Sustainable Development Goals.

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Appendix A

Table A1: Description of the five poverty measures used in the study

Poverty Measures	Description
Money-Metric	
Distribution Insensitive	
Headcount Index HH= $\left(h/n\right) \times 100$	where *h* is the number of poor people living below the poverty line and n is the total number of people. HH is the proportion of people living below the poverty line.
Poverty Gap Index , $\mathrm{PG} = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z-Y_i}{Z}\right)\times 100\right)}{n}$	where Z stands for Poverty Line and Y_i is individuals i's consumption. (if consumption is greater than poverty line then it is set equal to zero)
Distribution Sensitive	
Squared Poverty Gap , $\mathrm{SPG} = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z-Y_i}{Z}\right)^2 \times 100\right)}{n}$	where Z stands for Poverty Line and Y_i is individuals i's consumption. (if consumption is greater than poverty line then it is set equal to zero)
Multidimensional	
Distribution Insensitive	
Multidimensional Poverty Index MPI = M (α, k; y) = $\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right) I_{i}^{k} \times 100$	For *n* individuals and *d* total dimensions, $g_{ij}^{\alpha}=\left(1-y_{ij}/z_j\right)^{\alpha} I_{ij}$ for $\alpha \geq 0$ is the indicator for deprivation for an individual *i* in dimension *j*. z_j is the cut-off point for the dimension *j*. $I_{i}^{k} = I(C_i \geq k)$ is the poverty indicator in which *k* is the cut-off, number of dimensions in which an individual has to be deprived to be poor and C_i is the total dimensions in which an individual *i* is deprived. $C_i = \sum_{j=1}^{d} I_{ij}$
Distribution Sensitive	
Multidimensional Distribution-Sensitive Poverty Index MDPI = M (α, β; y) $= \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right)^{\beta} \times 100$ for $\alpha \geq 0$ and $\beta \geq 1$	For β > 1, the measure M(α, β; y) satisfies a cross-dimensional convexity axiom Where; $g_{ij}^{\alpha} = (1-\frac{y_{ij}}{z_j})^{\alpha} I_{ij} \quad for\ \alpha \geq 0$ $I_{ij} = I(y_{ij} < Z_j)$ 0 – 1 deprivation indicator function. and y_{ij} is the individual *i's* score in dimension *j* and z_j is the cutoff point for deprivation *j*. I_{ij} is zero when y_{ij}>z_j and 1 when $y_{ij} \leq z_j$

CHAPTER 6

What matters the most for money-metric and multidimensional rural poverty reduction? Big city growth or secondary town growth

6.1 Introduction

An inevitable part of the economic development process is increased urbanization, as part of the structural transformation away from agriculture and into industry and services. The classic studies on this topic (see Johnston (1970) for a review of the literature from this era) considers the urban sector as a whole. However, recent years have seen increased interest in separately examining effects of growth in big cities and growth in secondary towns. One argument is that supporting the development of secondary towns provides more options for the rural population to move out of agriculture than occurs if urban development is primarily focused on big cities. There are several reasons for this, including that it is cheaper to create jobs in secondary towns than in big cities (Kanbur et al., 2019) and that it is more feasible for rural migrants to settle into and find work in secondary towns (Ingelaere et al., 2018). Perhaps because of these factors, in at least some countries the growth of secondary towns appears to be more closely associated with rural poverty reduction than is the growth of big cities (Christiaensen et al., 2013).

A particularly pertinent case study of the contrasting effect on rural poverty of big city growth and secondary town growth comes from India. Over the last few decades, and especially since liberalization in 1991, the urban and rural economies of India have become more integrated, changing the pattern from one where urban growth primarily affected urban poverty reduction to one where urban growth also had positive effects on the rural sector (Datt et al., 2020). This pattern has been disaggregated by using night-time lights data to show India's urban growth and survey data to measure rural poverty, with the results suggesting that growth of secondary towns, especially on their extensive margin rather than their intensive margin, was more closely associated with rural poverty reduction than was growth of big cities (Gibson et al., 2017). A feature of these results was the use of spatial econometric models to recognize the links between nearby areas; for example, the elasticity of own-region poverty with respect to the poverty rate of neighbouring regions was 0.3 and the poverty rate for neighbours was always a significant predictor of own-region poverty in India. These spillovers meant that some of the beneficial effect of secondary town growth on reductions in rural poverty occurred indirectly and would not be picked up by empirical methods that treat each an area as independent of other areas.

The night-time lights data used to proxy for different types of urban growth in India are available for all countries, so it is interesting to see whether the same patterns hold elsewhere. In this chapter, I examine the effect on rural poverty in Pakistan from the growth of big cities and the growth of secondary towns. Urban growth is measured using satellite-detected night-time lights in as close a manner as possible to that used by Gibson et al. (2017) for India. The poverty measures available for rural households are for 100 districts, every second year from 2004 to 2014 (in contrast, the study in India was based on groups of districts, observed four times from 1993 to 2012).

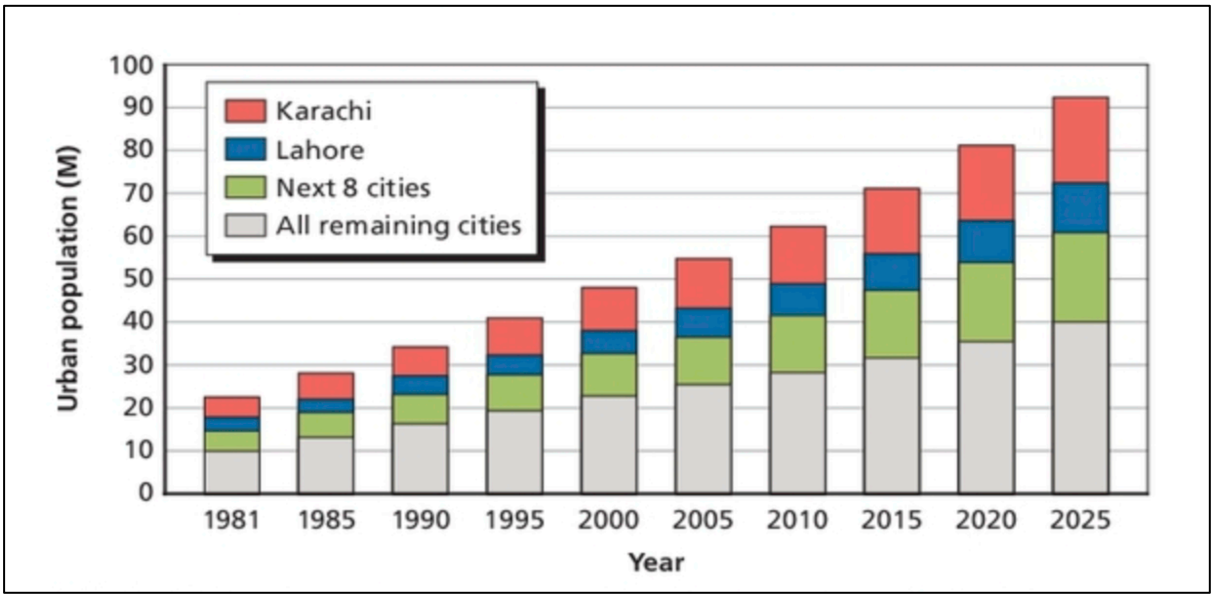
In addition to providing more evidence on the question of what type of urban growth is most closely related with rural poverty reduction, this chapter extends the literature by going beyond the traditional money-metric poverty measures, such as the *headcount index* (the share of the population living in households whose consumption or income is below the poverty line). A trend in many countries over the last few years has been to adopt multidimensional poverty measures (Alkire et al., 2011 UNDP, 2016) to either supplement or replace the traditional money-metric measures. Other poverty analyses for Pakistan show that results can be sensitive to using multidimensional and money-metric poverty measures. For example, Najam, (2020) found that temporal poverty trends at the district-level were not the same when using the multidimensional rather than the money-metric measures. Likewise, Najam and Gibson (2021) found that there was convergence in district-level poverty rates in Pakistan over the 2004-14 period, if money-metric poverty measures are used, but not if multidimensional measures are used. Thus, it is worth examining whether the relationship between urban growth and rural poverty reduction in Pakistan depends on the type of poverty measure used.

The rest of the chapter is set as follows: Section 2 provides background on urban development in Pakistan, with some evidence from the night-time lights data. Section 3 discusses the econometric methods and poverty data. Section 4 has the results and Section 5 concludes.

6.2 Urban Development in Pakistan: Background and Evidence from Night-time Lights

In Pakistan, there have been some essential development projects in place for the last two decades; key infrastructure projects like metro line, orange line, highways, flyovers and under-passes. However, most of these initiatives have been confined to the major big cities. The development initiatives have been more focused in Lahore (Rana et al., 2020). After the 7th National Finance Commission Award and Eighteenth Constitution Amendment, the provinces have the liberty to manage their finances and implement projects. The provinces now have the power and discretion to identify their respective regions that requires attention in terms of development and plan their projects accordingly. However, the capitals of the provinces have witnessed the most development. Lahore and Karachi, the capitals of Punjab and Sindh provinces respectively, have received the most attention for the development projects (Blank et al, 2014). Even the urbanization is seen in the small number of very large cities in Pakistan, UN has projected the urbanisation to continue majorly in big cities of Pakistan (United Nations, 2014) (see Figure 1). Whereas, the capitals of another two provinces, Quetta of Balochistan province and Peshawar of Khyber Pakhtunkhwa province have been growing relatively slowly because of the unrest and security risks in those two provinces. In Pakistan, because of the disparity observed in development projects and funding, the big cities are growing faster than the secondary towns. This is the same trend observed using night-time lights data, where big cities are growing faster than secondary towns.

Figure 1: Population growth in Pakistan's largest cities (1981 – 2025)



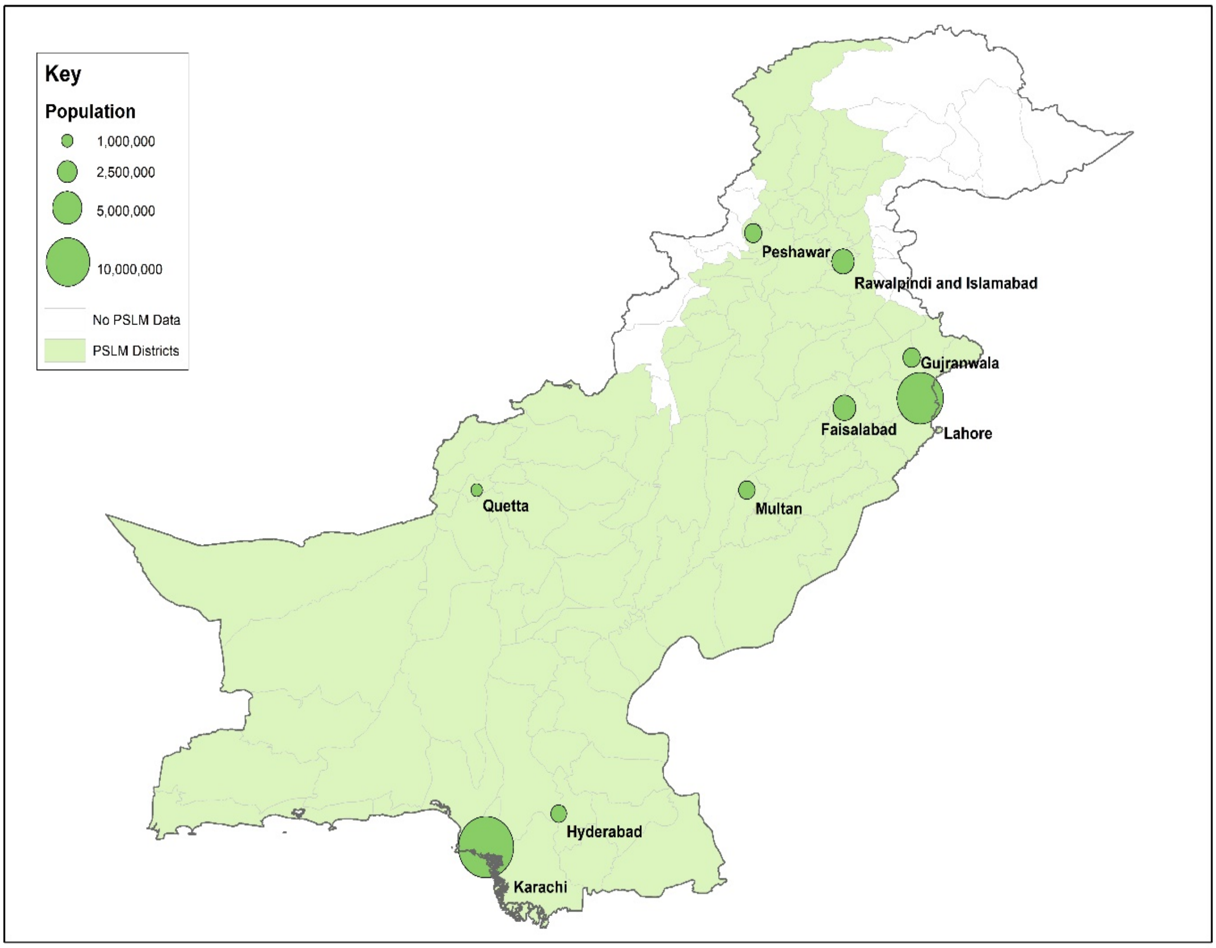
Source: Blank et al, 2014

The night-time lights data from the Defence Meteorological Satellite Program (DMSP) are widely used to study economic growth, particularly of urban areas (see Gibson et al., 2020, for a review). These data were originally processed by the National Oceanic and Atmospheric Administration (NOAA) and provide annual composites from 1992 onwards (for most years prior to 2008, two satellites were in orbit in the same year so there are two estimates per year). The data provided are a Digital Number (DN), that ranges from 0 to 63, where 63 is the value for the areas with the brightest lights, and are presented on an output grid of 30 arc-seconds, which is approximately one km^2 at the equator (Baugh et al., 2010).

In the Gibson et al. (2017) study on India, there were 47 big cities, defined at a threshold of a population above one million in the 2011 census (some of these, such as New Dehli, include nearby cities engulfed into one large conurbation). The area of these cities in each year was measured with DMSP data, where cities were demarcated from other lit areas by using a luminosity threshold of 50 percent of the maximum DN value (where this particular value was based on cross-validation exercises from Gibson et al. (2015)). To measure the lit area each year, an algorithm was used that started at the center of each big city, where lights should be brightest, and as it moved outwards and came across pixels less illuminated than the brightness threshold it searched in a different direction. If the algorithm found no contiguous pixels with DN values above the threshold, except those closer to the city center that it has already scanned over, it set a boundary for the big city area in that year.

While the big cities were measured starting from a defined point (such as the central railway station), the secondary towns were measured in a different way. All lit areas above thresholds of either 20 percent or 30 percent of the maximum luminosity, but excluding the area taken up by the big city in each year, were added together for each district. These 20 percent and 30 percent values distinguished towns from less brightly-lit villages and rural areas, and with these two types of urban areas, big cities and secondary towns, defined, urban growth was divided into two components. The growth on the extensive margin was based on the expansion in the lit area each year, while growth on the intensive margin was based on the average DN value (that is, on brightness) within the lit area. In India, the dominant driver of rural poverty reduction was growth on the extensive margin, especially of the secondary towns.

Figure 2: Location map for the nine big cities used in the analysis



Source: Authors calculation

In this chapter, I apply the same approach to Pakistan, using a threshold of population above one million to define big cities. In 2017 there were ten such cities; six in Punjab (Lahore, Faisalabad, Rawalpindi, Gujranwala, Multan and Islamabad), two in Sindh (Karachi and Hyderabad), and one each in Balochistan (Quetta) and Khyber Pakhtoonkhwan (Peshawar). The DMSP data show that Rawalpindi and Islamabad have merged into one lit area in each year of the 2004-14 period studied, so the analysis is based on nine big cities, (see Figure 2). With 100 districts having data on rural poverty from the PSLM survey, this gives an 11:1 ratio of districts to big cities, which is about the same as for the Gibson et al. (2017) analysis for India, where there are approximately 500 districts (and 47 big cities). Also, the population of India is somewhat more than six times that of Pakistan, so nine big cities in Pakistan also translates into about 50 in India, which is around the number used in the analysis by Gibson et al. (2017).

There are important differences between India and Pakistan in urban development, as detected from the night-time lights data. A compilation of national level DMSP lights, for each year from 1992 to 2012 (Elvidge et al., 2014), shows that in India the trend annual growth rate in night-time lights was 2.7 percent, while in Pakistan it was only 1.5 percent (the *t*-statistics - based on standard errors robust to heteroscedasticity and autocorrelation - for rejecting the null hypothesis that the trend rate of increase is zero are 2.7 for India and 1.9 for Pakistan). These growth rates imply doubling times of 26 years for India and 47 years for Pakistan, so it is evident that overall urban growth has been rather slower in Pakistan than in India. Moreover, the pattern of growth appears to be different, with urban growth in Pakistan due more to the big cities while in India it was due more to the secondary towns. Specifically, using the approach to measuring the area of big cities and secondary towns described above, between 2004 and 2012, the area of the big cities in India grew by 101 percent while the increase for secondary towns was much faster, 174 percent (see Table 1).[21] In Pakistan the increase in area of big cities was 48 percent while it was only 37 percent for secondary towns. Given that Pakistan's secondary towns seem to be growing far more slowly than India's secondary towns, when using the same measurement approach in each country, the relationship between different types of urban growth and rural poverty reduction may not be the same in each country.

Table 1: Growth in Lit Area for Big Cities and Secondary Towns, 2004-2012

	India (%)	Pakistan (%)
Big cities	101	48
Secondary towns	174	37

Notes: Secondary towns are defined as lit areas above a 30% luminosity threshold, excluding the lit areas of big cities. The values in the table are the 2012 area as a percentage of the 2004 area.

6.3 Data and Econometric Methods

6.3.1 Poverty Estimates

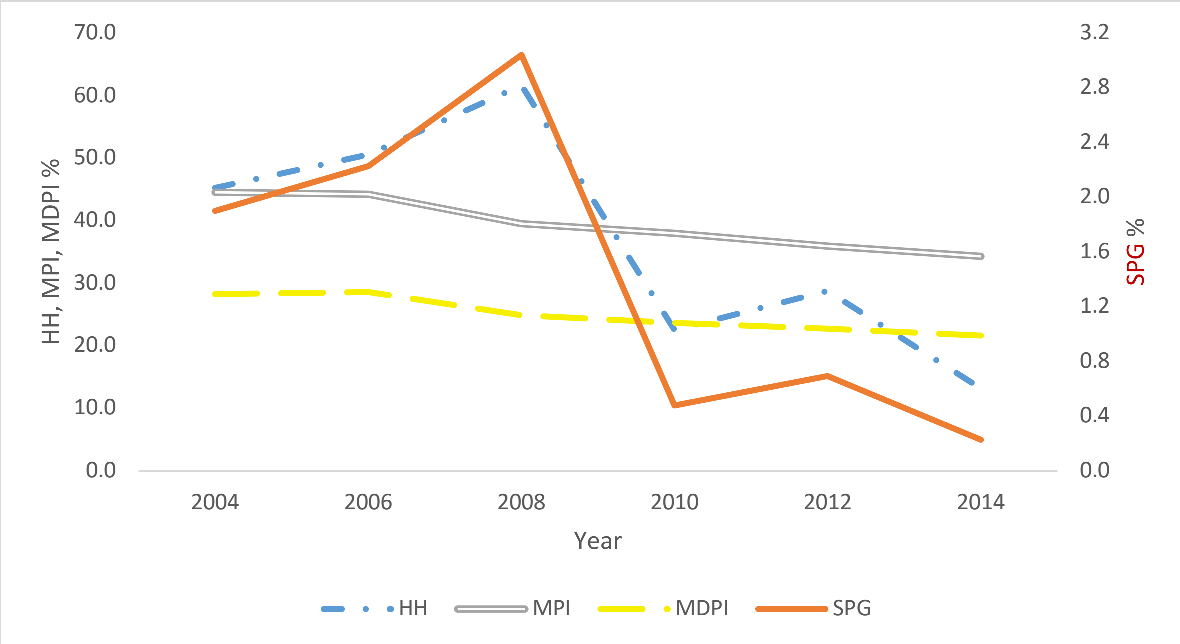
The four indicators of rural poverty used in this chapter are two money-metric indicators: the headcount index (HH), and the squared poverty gap index (SPG). The SPG is a distributionally sensitive measure, that puts more weight on the people furthest below the poverty line, while HH is not distributionally sensitive. The other two measures are the MPI, based on Alkire and Foster (2011), and the multidimensional distribution-sensitive poverty index (MDPI)

[21] The values for India are from Table 2 of Gibson et al (2017), for secondary towns defined by a 30% luminosity threshold, and relate to the 2004/05 and 2011/12 years, while for Pakistan they are for 2004 and 2012. However, for both countries the values are based on averaging the values from DMSP satellites over two years centred on the timing of the survey, which should improve the cross-country comparability.

developed by Datt (2019). Thus, there are two multidimensional measures and two money-metric measures; two that are distributionally sensitive and two that are not. Detailed formulae for these four measures are given in Appendix A, while the data and methods for how they are constructed are described in Appendix B.

A brief summary of the construction of these poverty measures is that for the money-metric measures, an Elbers et al. (2003) survey-to-survey imputation approach is used to project the consumption data for rural households in the Household Income and Expenditure Surveys (HIES) onto the rural sample of the Pakistan Social and Living Standards Measurement Surveys (PSLM) that lack consumption data, using sets of predictor variables from the two surveys that overlap (see Dang et al. (2019) for a review of these projection methods). The PSLM surveys are representative at district-level, and are used to directly calculate the multidimensional poverty measures. The resulting database of rural poverty measures is available for 100 districts (using a consistent spatial definition of districts from 2004 to account for the subsequent splitting of some districts), every second year from 2004 to 2014.

Figure 3: Average district-level poverty estimates of rural regions

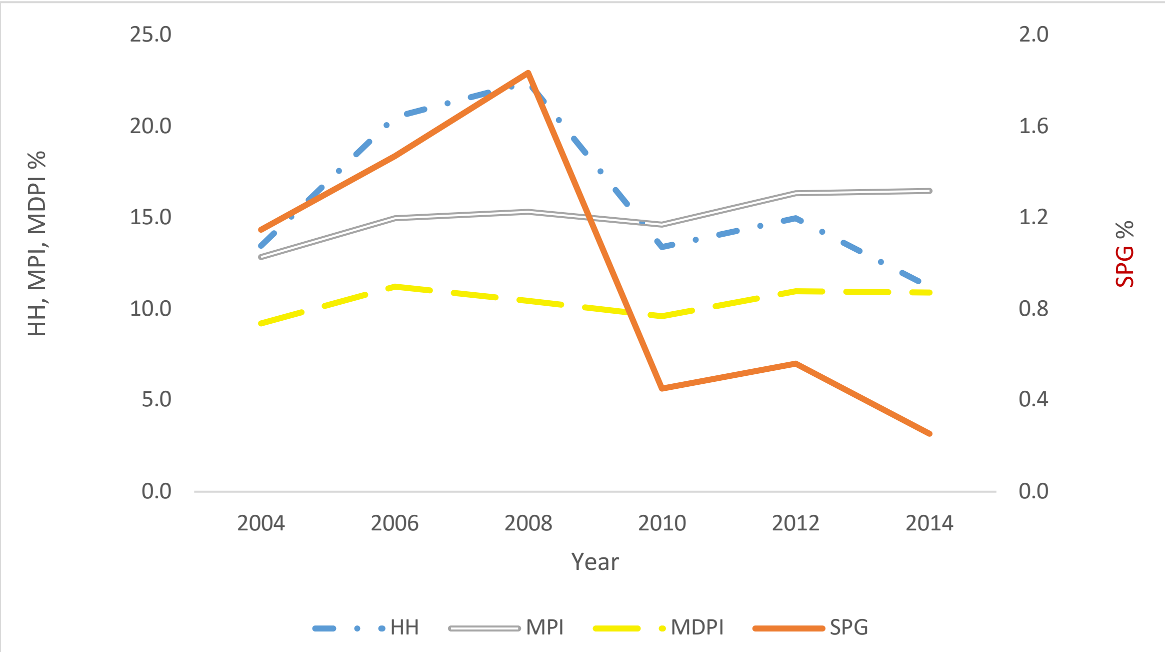


Source: Najam (2020)

The patterns of rural poverty revealed by these indicators is shown in Figures 3 and 4. The money-metric poverty measures for the rural regions of the districts show an increasing trend up until 2008 and start to fall after, whereas the multidimensional poverty indicators have shown a declining trend for the period of 10 years (see Figure 3). The money-metric poverty measures which are based on consumption show a peak at 2008, the year where the prices for the staple crops soared (Gibson & Kim, 2013) and inflation in Pakistan peaked at 20 percent. The rural poverty rates (consumption based) are affected because the rural population in Pakistan is agriculture dependent.

The standard deviation of rural regions in districts for multidimensional poverty measures is slightly increasing (see Figure 4), meaning that, although the average multidimensional poverty is decreasing with time, the disparity in access to services and facilities is increasing. For money-metric poverty measures the disparity in consumption levels across rural regions of districts increases as the average poverty estimates increase. The economics shocks that have led to the increase in average poverty estimates have also increased the disparity at the same time.

Figure 4: Standard Deviation of district-level poverty estimates of rural regions



Source: Najam (2020)

The spatial profile of the rural regions of the districts for the years 2004 and 2014 and the change in poverty from 2004 to 2014 are shown in Appendix C. In 2004, the rural regions of the districts in south Punjab and Sindh were the poorest in terms of money-metric poverty (see Figure C1), whereas the rural regions in the south of Pakistan, Balochistan and Sindh were the poorest in terms of multidimensional poverty. In 2014, the rural regions of Balochistan became the poorest as per money-metric poverty measures as they have not caught up in reducing poverty (see Figure C2). This is clear from Figure C3, where the least reduction in money metric poverty measures is seen for Balochistan and Sindh districts. There is one thing to note, the districts which have shown the least reduction in poverty whether money-metric or multidimensional poverty, are farthest from the big cities.

6.3.2 Econometric Methods

A general-to-specific spatial econometric regression modelling strategy is used. The maps of the district-level rural poverty rates suggest considerable non-randomness over space, with nearby areas having similar poverty rates. The spatial econometric models can account for this pattern, and also provide a way to incorporate spillovers where urban growth in one place might affect rural poverty in many districts. The district-level *N*-vector of poverty measures for date *t* (=1,…,*T*) is denoted P_t and the matrix of explanatory variables based on the night-time lights derived indicators is X_t. The most general starting model is a Spatial Autoregressive Model with Autoregressive Errors (SARAR):

$$P_t = \delta W P_t + X_t\beta_1 + WX_t\beta_2 + \mu + t + \varepsilon_t \qquad (i = 1, \cdots, N; t = 1, \cdots, T) \quad \text{(1a)}$$

$$\varepsilon_t = \rho W \varepsilon_t + v_t \quad \text{(1b)}$$

Here the spatial weighting matrix *W* describes the structure of spatial relationships between the 100 districts in the sample (which covers almost all of Pakistan other than some border areas where the security situation did not allow the surveys to be implemented). The *W* matrix has zeros along the main diagonal, given that no district is its own neighbour, while (to allow for geographic spillover effects) the off diagonals are set to unity for immediate neighbours and zero otherwise using Queen contiguity weights. With this model, changes in an explanatory variable in a particular district not only affect the poverty rate in that district, but also in nearby districts. If the estimate of the δ coefficient is non-zero, these spillovers will occur globally, while if δ is zero and β_2 is non-zero then the spillovers occur locally.

The error term has three components. The term μ represents any time-invariant fixed effects, that will reflect latent factors specific to a particular district that are relatively constant over time. The term t represents time fixed effects, that are specific to any of the six survey years (2004, 2006, 2008, 2010, 2014). Finally, the remaining part of the error, ε_t is allowed to have a potential correlation, shown by the ρ coefficient, with the error terms for nearby districts, based on the spatial lag of the errors, $W\varepsilon_t$. The resulting panel data model with spatially correlated error components (Kapoor et al., 2007) should provide appropriate inferences that account for any spatial autocorrelation in the errors.

The model set out in equations (1a) and (1b) is a very general one that nests several other commonly used models. If $\rho = 0$ the resulting model is a spatial Durbin model that has lags of the outcome variable and of the right-hand side variable (the model used by Gibson et al. (2017) in their study for India). A spatial autocorrelation model results if $\beta_2 = 0$, which then gives a model with spatial lags of the dependent variable and spatial lags of the errors. The spatial auto-regressive model (*aka* the spatial lag model) results if $\beta_2 = \rho = 0$, where only the dependent variable is spatially lagged. A spatial error model results if only errors are spatially lagged (so $\delta = \beta_2 = 0$).

A feature of these models, other than the spatial error model, is that the spatial lags imply that there are spillovers. Specifically, shocks to the right-hand side variable in one district may propagate through the observations for other districts and cause a total impact that may exceed the initial direct impact given by the β_1 coefficient. These total impacts can be decomposed into direct and indirect components (LeSage & Pace, 2009). This decomposition relies on estimating a 100×100 matrix of cross-partial effects (given our sample has 100 districts). Each cell in this matrix shows the relationship between rural poverty in district *i* and the change in the urbanization indicator in the j^{th} district. However, this additional post-estimation step is only needed if either the lags of the dependent variable or of the independent variables are statistically significant (as lags of the errors do not generate spillovers).

In order to estimate equation (1), the four poverty measures discussed in Section 3.1 are used (sequentially) as the dependent variable. A vector of four urban growth variables is used in the X_t matrix: big city lit area and average DN value, and secondary town lit area and average DN value. For the secondary town lit area and average DN value each year, variables are constructed directly at the district-level. A different method is used for the big city variables, to link each of the 100 districts to the nine big cities. The geographic centroid of each district is estimated and the inverse of the distance from that centroid to the centroid of each of the big cities is used as a weight, and then a weighted average of the big city variables is constructed for each district. In other words, the effect of big city growth on a district is more heavily weighted to the patterns shown by the nearby big cities: so for example, districts near Peshawar, which had the slowest growth of any big city and in some periods even showed some decline, will have a smaller big city growth component than districts near Lahore and Rawalpindi (and

Islamabad), which are the two big cities exhibiting the fastest growth.

The two final data steps before reporting the estimated results deal with zeroes in the night-time lights data for secondary towns and with the standardization of variables to enhance the comparability of coefficient estimates. When secondary towns are defined by using a 20 percent luminosity threshold, 11 districts have some years where there are no lit areas with DN values above the threshold, while at a 30 percent threshold there are 14 such districts. The presence of zeroes prevents taking the logarithms of the variables, so an inverse-hyperbolic sine transformation is used instead, which is equivalent to logarithms for the non-zero values but allows observations with a zero to be included as well. There are sensitivity results from Gibson et al. (2017) for India that show that the inverse hyperbolic sine transformation gives identical elasticities to those obtained using logarithms. The second data transformation was to standardize all of the variables, which aids comparability given that some are in units of square kilometers and others are in DN values, while standardization allows the coefficients to be interpreted in terms of equivalent sized effects (standard deviation changes).

6.4 Results

The results of estimating equation (1) with the four poverty variables are reported in Table 2. There are no statistically significant effects of the secondary town variables, and all but one of the spatial lags of those variables (the spatial lag of lit area, in the regression for the headcount poverty rate) are also statistically insignificant. The big city lit area (for the squared poverty gap) and the average DN value for big cities (for the two multidimensional poverty measures) are statistically significant but with positive coefficients, suggesting that rural poverty is higher in places where nearby big cities are growing faster. All but one of the spatial lags of the big city variables (for lit area, in the regression for MDPI) are also statistically insignificant. Given these statistically insignificant spatial lags of the variables in the X_t matrix, a test that these lags can be excluded is not rejected in any case (see the last row of Table 2).

Table 2: SARAR Model Results for Effects of Urban Growth on Rural Poverty in Pakistan: 2004-14

	Poverty Indicator			
Variables	HH	SPG	MPI	MDPI
Big city lit area	-0.250	0.419	-0.097	0.159
	(1.21)	(2.47)**	(0.66)	(1.07)
Big city average DN value	-0.202	0.008	0.193	0.273
	(1.47)	(0.07)	(1.95)*	(2.73)***
Secondary town lit area	0.014	-0.076	-0.066	-0.077
	(0.07)	(0.44)	(0.46)	(0.52)
Secondary town average DN value	-0.113	0.090	0.030	0.057
	(0.69)	(0.66)	(0.26)	(0.49)
W × Big city lit area	-0.053	-0.034	-0.020	-0.029
	(1.52)	(1.15)	(1.15)	(1.65)*
W × Big city average DN value	-0.033	-0.023	0.014	-0.007
	(0.86)	(0.75)	(0.83)	(0.43)
W × Secondary town lit area	0.191	0.154	0.023	0.020
	(1.71)*	(1.63)	(0.31)	(0.28)
W × Secondary town average DN value	-0.141	-0.043	0.006	0.022
	(1.58)	(0.57)	(0.09)	(0.36)
Spatial lag of poverty rate	-0.048	-0.038	-0.033	-0.039
	(2.34)**	(2.10)**	(1.13)	(1.25)
Spatial lag of errors	0.148	0.157	0.106	0.093
	(21.51)***	(35.60)***	(5.62)***	(4.20)***
Pseudo-R^2	0.351	0.386	0.178	0.061
Test that spatial lags of indep variables = 0	4.76	7.58	4.13	4.53

Notes: The four poverty variables are HH (headcount index), SPG (squared poverty gap index), MPI (multidimensional poverty index) and MDPI (multidimensional distributionally sensitive poverty index). Secondary towns are defined according to a 20% luminosity threshold. Each regression includes fixed effects for 100 districts and for six years. All variables are in logarithms (using the inverse hyperbolic sine transformation to deal with zeros) and standardized. The test for the spatial lags of independent variables=0 is distributed as chi-squared (4 df). Statistical significance of coefficients is based on z-tests in ( ) with ***, **, * denoting significance at 1%, 5% and 10% levels.

The results of spatial autocorrelation models are reported in Table 3, where these are the next step in the general-to-specific modelling sequence, based on excluding the spatial lags of the variables in the X_t matrix. With the irrelevant spatial lags omitted, there is somewhat more precision in the estimates of the reduced set of coefficients, although they continue to present a mixed picture. For the headcount index, there is a negative relationship between big city average DN values and rural poverty and also a negative (but statistically insignificant at the p<0.10 level) relationship with big city lit area. For the squared poverty gap, big city lit area is positively associated with the rural poverty rate while for secondary town lit area it is a negative

Table 3: Spatial Autocorrelation Model of Effects of Urban Growth on Rural Poverty in Pakistan: 2004-14

	Poverty Indicator			
Variables	HH	SPG	MPI	MDPI
Big city lit area	-0.304	0.393	-0.157	0.054
	(1.48)	(2.31)**	(1.17)	(0.40)
Big city average DN value	-0.251	-0.035	0.193	0.219
	(1.89)*	(0.32)	(2.24)**	(2.54)**
Secondary town lit area	-0.206	-0.272	-0.104	-0.119
	(1.21)	(1.96)**	(0.76)	(0.84)
Secondary town average DN value	0.048	0.154	0.042	0.071
	(0.35)	(1.39)	(0.38)	(0.62)
Spatial lag of poverty rate	-0.028	-0.027	0.001	0.000
	(1.85)*	(1.76)*	(0.05)	(0.01)
Spatial lag of errors	0.143	0.154	0.084	0.066
	(20.50)***	(30.33)***	(3.76)***	(2.54)**
Pseudo-R^2	0.399	0.449	0.267	0.172

Notes: See Table 2.

relationship. For the two multidimensional indicators, the only two statistically significant terms from the night-time lights data are a positive relationship between big city average DN values and multidimensional rural poverty.

The spatial autocorrelation models in Table 3 include a spatial lag of the dependent variable, and if the coefficient on this spatial lag is statistically significant it implies that there are global spillovers. For the multidimensional measures, the spatial lag of the poverty rate has a coefficient that is zero, and so if the LeSage and Pace (2009) decomposition of indirect and direct effects is carried out, all of the indirect effects have *z*-test values that are close to zero (0.05 for MPI: 0.01 for MDPI). For the money-metric poverty measures, the spatial lags do have statistically significant coefficients (at the $p<0.10$ level), but these are negatively signed and meaning that the total impacts (which take account of indirect effects through spillovers) are slightly closer to zero than are the direct impacts given by the β_1 coefficient. None of the indirect impacts' terms for the headcount and squared poverty gap models are statistically significant (the most precise is a negative indirect effect of big city lit area on the squared poverty gap, which has a *z*-test value of -1.48 for $p<0.15$). In contrast to the statistically weak evidence for spatial lags of the dependent variable in the models for money-metric poverty, the spatial lag of the errors is statistically significant (at $p<0.01$ level) in the models for all four of the poverty measures. This pattern suggests that the specification that is most consistent with the data is a spatial error model.

The results of spatial error models are reported in Table 4. A feature of these models is that there are no indirect effects from spillovers, so the impact of various types of urban growth on rural poverty can be ascertained directly from the coefficient values in the table and there is no need for the LeSage and Pace (2009) decomposition. It appears that big city growth, in terms of brightness (average DN values) is associated with a lower headcount rate for rural poverty but higher rates of multidimensional poverty. In contrast, growth in the lit area of the secondary towns is associated with lower rural poverty according to the squared poverty gap index while no other indicator of rural poverty has a statistically significant relationship with either the lit area or the average DN value of secondary towns.

Table 4: Spatial error models of effects of urban growth on rural poverty in Pakistan: 2004-14

	Poverty Indicator			
Variables	HH	SPG	MPI	MDPI
Big city lit area	-0.315	0.404	-0.156	0.054
	(1.54)	(2.28)**	(1.16)	(0.41)
Big city average DN value	-0.241	0.002	0.195	0.219
	(1.84)*	(0.02)	(2.32)**	(2.69)***
Secondary town lit area	-0.192	-0.289	-0.105	-0.119
	(1.10)	(2.16)**	(0.78)	(0.84)
Secondary town average DN value	0.027	0.154	0.042	0.071
	(0.19)	(1.43)	(0.39)	(0.63)
Spatial lag of errors	0.135	0.186	0.085	0.066
	(21.12)***	(133.45)***	(7.88)***	(5.54)***
Pseudo-R^2	0.397	0.441	0.266	0.172

Notes: See Table 2.

Overall, the evidence shown in Table 4 is far more mixed than was the evidence for India, where growth of secondary towns was consistently associated with lower rural poverty rates, for money-metric poverty indicators, and there was no apparent effect of big city growth on rural poverty. It is important to note that the results in Tables 2-4 are based on a definition of secondary towns that uses a luminosity threshold of 20 percent. As a sensitivity analysis, the models were re-estimated using a luminosity threshold of 30 percent, with the detailed results reported in Appendix D.

The results are similar to those observed using 20 percent luminosity threshold. Using the generalised spatial regression model (see Table D1), there are no statistically significant effects of the secondary town variables. The big city lit area (for the squared poverty gap) and the average DN value for big cities (for the two multidimensional poverty measures) are statistically significant but with positive coefficients. All but one of the spatial lags of the big city variables (for lit area, in the regression for MDPI) are also statistically insignificant. Given the insignificant spatial lag independent variables, Spatial Autoregressive model is estimated (see Table D2). For the headcount index, there is a negative relationship between big city average DN values and rural poverty and also a negative (but statistically insignificant at the $p<0.10$ level) relationship with big city lit area. For the squared poverty gap, big city lit area is positively associated with the rural poverty rate while for secondary town lit area it is a negative relationship. For the two multidimensional indicators, the only statistically significant relationship is a positive relationship between big city average DN values and multidimensional rural poverty. The spatial lag of poverty is significant for only money metric poverty measures in which the indirect impacts for Headcount are insignificant. However, for SPG, the indirect impact of big city lit area, secondary town lit area and DN values on poverty is significant. This means the total impact (direct and indirect) of increasing big city lit area and secondary town DN value on neighbouring districts' rural areas is poverty (SPG) increasing, whereas the increasing secondary town lit area is SPG decreasing for rural areas of the neighbouring districts.

In Table D3, because of the insignificant spatial poverty lag in the model and highly significant spatial error lag term, spatial error model is estimated. The big city growth, in terms of brightness (average DN values) is associated with a lower money-metric headcount rate for rural poverty but higher rates of multidimensional poverty. However, neither the lit area nor the brightness of the secondary town is associated with the lower rural poverty except if poverty is calculated using squared poverty gap. The growth in secondary towns calculated through the lit area is impactful in reducing rural poverty (squared poverty gap index) of neighbouring districts.

6.5 Discussion and Conclusion

In recent years there has been increased interest in separately examining effects of growth in big cities and growth in secondary towns. The rationale behind is that the development of secondary towns provides rural population with more job opportunities than the development of big cities. The analysis on the district-level of Pakistan has unravelled some intriguing relationships between urban growth and rural poverty reduction. In my knowledge there is no study in the literature which has analysed the impact of urban area growth separately for secondary town and big cities on rural poverty alleviation, more so using both money-metric and multidimensional poverty measures. This study contributes to providing evidence base for the impacts of growth in big cities and secondary town on reducing rural poverty. With growing interest in multidimensional poverty measures it is imperative to research if the growth in secondary towns and big cities is equally impactful in reducing multidimensional and conventional money-metric poverty of rural population.

In Pakistan the secondary town growth has been slower than in the big cities. Pakistan has been through the slow growth spells post 2004 (when the GDP growth was highest) which might have affected the urban growth in particular secondary towns. For the analysis, both extensive and intensive margins are considered for big cities and secondary town growth because it is a priori unclear which matters more for the rural poverty reduction. In the case of Pakistan, the intensive margins (average DN values) of the big cities are not poverty reducing except for the money-metric headcounts, whereas headcount is a crude poverty indicator, that does not measure the depth or intensity of impoverishment. The extensive margins (lit area) of big cities are poverty reducing for only distribution-insensitive poverty measures (HH and MPI), although the impact is statistically insignificant. For the secondary town, the growth in intensive margin (average DN value) is poverty reducing for money-metric headcount only, although statistically insignificant. The extensive margin (lit area) for secondary town is associated with rural poverty reduction, both for multidimensional and money-metric, however, it is significant only for the squared poverty gap index which captures the intensity and depth of money-metric impoverishment.

Except for the headcount index, the growth in big cities is not poverty reducing, instead for rural multidimensional poverty it is poverty increasing. It is because as per the population demarcation of 1 million, I have 10 big cities and 8 of them are in the north of Pakistan whereas the most impoverished segment of population is concentrated in the south. Having all the resources and growth concentrated in one region makes it difficult for the rest of the regions to benefit from that growth, given the distance between the two. Particularly, the multidimensional poverty indicators which measure the access to quality education and health services have shown significant poverty increasing impact of big cities growth (intensive margins). Given the slow growth of secondary towns, especially on the extensive margins, its poverty reducing impact on multidimensional poverty is insignificant. However, this slow growth in towns (extensive margins) is significant in reducing squared poverty gap index. Hence, the sprawling of secondary towns is influential in providing economic and employment opportunities for the neighbouring rural population. So, for the urban growth to have an impact on people who are living far below the poverty line in rural regions, the growth must come from sprawling secondary towns. Whereas, only to pull the people out of money-metric poverty, who are close to the poverty line, the growth in big cities is significant in the context of Pakistan.

There are two conclusions which can be drawn from the analysis in this chapter. First, the impact of growth in extensive and intensive margins of big cities and secondary towns is sensitive to the dimensionality and distribution sensitivity in poverty measures. Second, when the target population is the one living far below the poverty line and is deprived in many dimensions, the growth in secondary town and specifically the sprawling towns is poverty reducing. Therefore, the policy makers need to focus on policies and development plans which are not only focused on big cities but also on the secondary towns so that the neighbouring rural regions can capitalise on that growth.

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Appendix A

Table A1: Description of the four poverty measures used in the study

Poverty Measures	Description
Money-Metric	
Distribution Insensitive	
Headcount Index HH= $\left({}^{h}/_{n}\right) \times 100$	Where *h* is the number living below the poverty line and n is total population. HH is the proportion of people living below the poverty line.
Distribution Sensitive	
Squared Poverty Gap , $\text{SPG} = \dfrac{\left(\sum_{i=1}^{n}\left(\frac{Z-Y_i}{Z}\right)^2 \times 100\right)}{n}$	As for the Poverty Gap Index
Multidimensional	
Distribution Insensitive	
Multidimensional Poverty Index $\text{MPI} = \ \text{M}\,(\alpha,\ \text{k};\ \text{y}) = \frac{1}{n}\sum_{i=1}^{n}\ \left(\frac{1}{d}\sum_{j=1}^{d} g\,{}_{ij}^{\alpha}\right) I\,{}_{i}^{k} \quad \times 100$	For *n* individuals and *d* total dimensions, $g\,{}_{ij}^{\alpha}$=$\left(1-y_{ij}/z_j\right)^{\alpha}\ I_{ij}$ for $\alpha \geq 0$ is the indicator for deprivation for an individual *i* in dimension *j* z_j is the cut-off point for the dimension *j*. $I\,{}_{i}^{k} = I(C_i \geq k)$ is the poverty indicator in which *k* is the cut-off number of dimensions in which an individual has to be deprived to be poor and C_i is the total dimensions in which an individual *i* is deprived. $C_i = \sum_{j=1}^{d} I_{ij}$
Distribution Sensitive	
Multidimensional Distribution-Sensitive Poverty Index $\text{MDPI} = \text{M}\,(\alpha,\ \beta;\ \text{y})$ $= \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g\,{}_{ij}^{\alpha}\right)^{\beta} \times 100$ for $\alpha\ \geq\ 0$ and $\beta\ \geq 1$	For β > 1, the measure M(α, β; y) satisfies a cross-dimensional convexity axiom Where; $g_{ij}^{\alpha} = (1-\frac{y_{ij}}{z_j})^{\alpha} I_{ij} \quad for\ \alpha\ \geq 0$ $I_{ij} = I(y_{ij} < Z_j)$ 0 – 1 deprivation indicator function. and y_{ij} is the individual *i's* score in dimension *j* and z_j is the cutoff point for deprivation *j*. $I_{ij}$is zero when y_{ij}>z_j and 1 when $y_{ij}\ \leqslant\ z_j$

Appendix B

PSLM and HIES are conducted on alternate years, the sample size for PSLM is six times of HIES (see Table B1 below). PSLM is representative at District-level which gathers information about education, health, fertility, and access to basic services but not about expenditure/income. HIES is representative at Provincial level which gathers information about education, health, access to services, income, and expenditure.

Multidimensional indices are calculated directly from PSLM at the district-level. Three broad dimensions are used to construct multidimensional indices: education, health and living standards. In the dimension of education, Years of schooling, Child School attendance, and School quality are considered. In the dimension of health, access to health facilities like Basic Health Units (BHU), immunization, ante-natal care, and assisted delivery are used. In the dimension of living standards water, sanitation, walls, overcrowding, electricity, cooking fuel, assets, and land and livestock (only for rural areas) are considered.

To calculate money-metric indices at the district-level, Small Area Estimation Technique is used. Therefore, HIES data from 2004-05, 2005-06, 2007-08, 2010-11, 2011-12, and 2013-14 has been used to impute consumption for households in the PSLM that were surveyed in 2004-05, 2006-07, 2008-09, 2010-11, 2012-13, 2014-15 respectively.

Given the different consumption patterns for rural and urban regions, consumption is estimated separately for rural and urban regions from HIES. Using HIES data, the consumption is regressed separately for urban and rural regions on variables like household size, gender, and years of schooling of the household head, the number of people in different age brackets, employment status of family members, the number of females in the household, ownership of various durable assets, access to services, dwelling status and facilities, and regional dummies. The variables are selected which have same distribution for HIES and PSLM in their respective years. After selecting the regressors / variables, the coefficients from the consumption regressions are used to impute consumption into PSLM data. The imputed consumption is then used to calculate money-metric poverty estimates at the district-level. This exercise is done separately for all six years. The R sq of consumption models for the urban and rural areas for all six years lie between 43 percent to 75 percent (see Table B1 below). The methodology is discussed in detail by Najam (2020).

Table B1: Survey details and R Sq of Beta Model (Rural and Urban) from SAE for all six years

Years	Surveys	Survey Period	Sample Size			R Sq Consumption model (%)	
			Total	Urban	Rural	Rural	Urban
2004-05	PSLM	Sep 04 - Mar 05	76520	27144	49376	45	67
	HIES	Jul 04 - Jun 05	14673	5794	8879		
2005-06	PSLM						
	HIES	Jul 05 - Jun 06	15453	6240	9213		
2006-07	PSLM	Oct 06 -May 07	73953	26273	47680	43	50
	HIES						
2007-08	PSLM						
	HIES	Jul 07 -Jun 08	15512	6255	9257		
2008-09	PSLM	Aug 08 - Jun 09	75772	26975	48797	43	50
	HIES						
2009-10	PSLM						
	HIES						
2010-11	PSLM	Jul 10 - Jun 11	77488	27360	50128	50	76
	HIES	Jul 10 - Jun 11	16341	6589	9752		
2011-12	PSLM						
	HIES	Sep 11 - Jun 12	15807	6743	9064		
2012-13	PSLM	Oct 12 - Jun 13	75516	26598	48918	44	54
	HIES						
2013-14	PSLM						
	HIES	Aug 13 - Jun 14	17985	6234	11751		
2014-15	PSLM	Oct 14 - Jun 15	78635	13965	64670	63	75
	HIES						

Source: Najam (2020)

Figure C1: Poverty estimates for rural areas of the districts in 2004

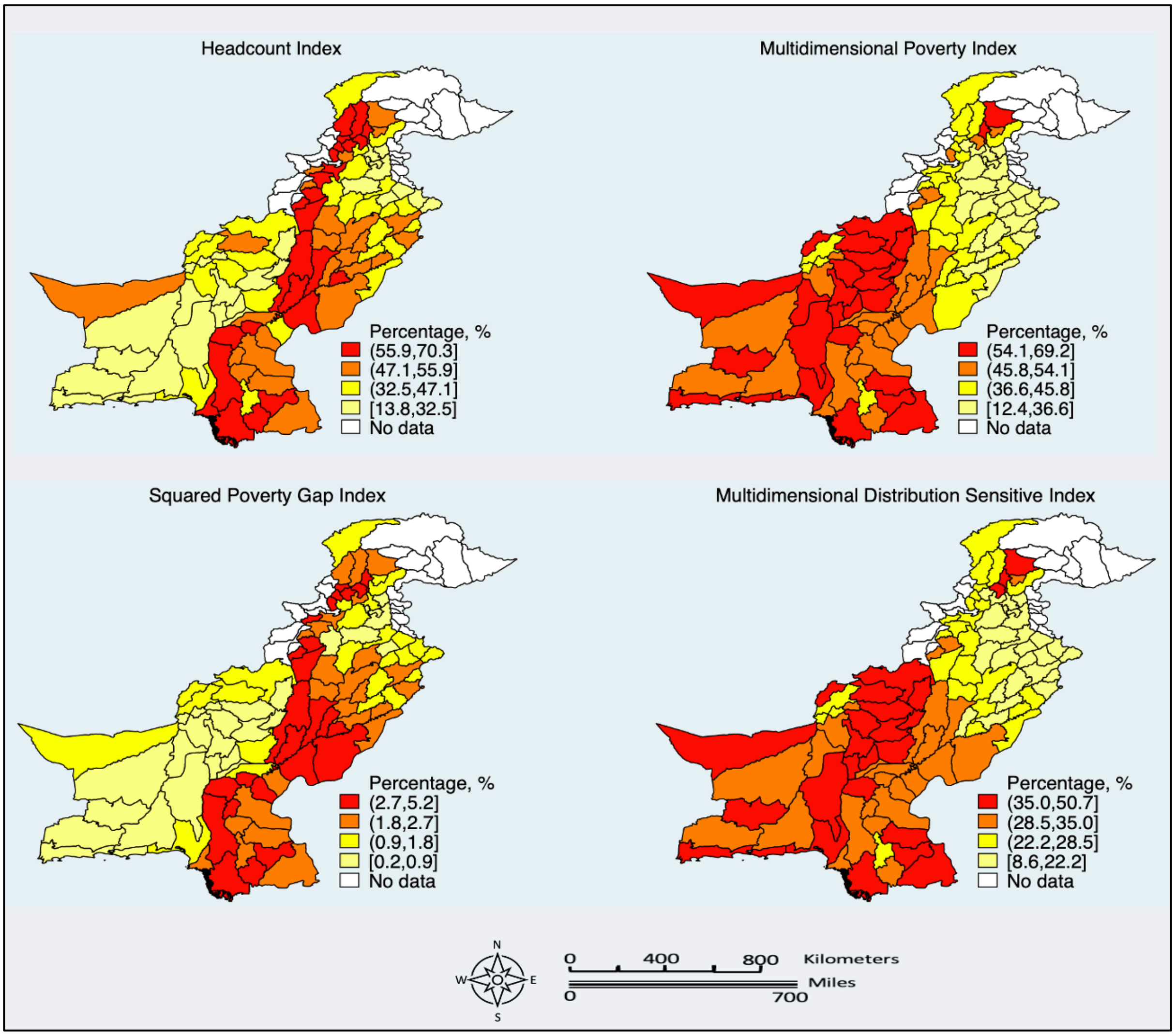


Figure C2: Poverty estimates for rural areas of the districts in 2014

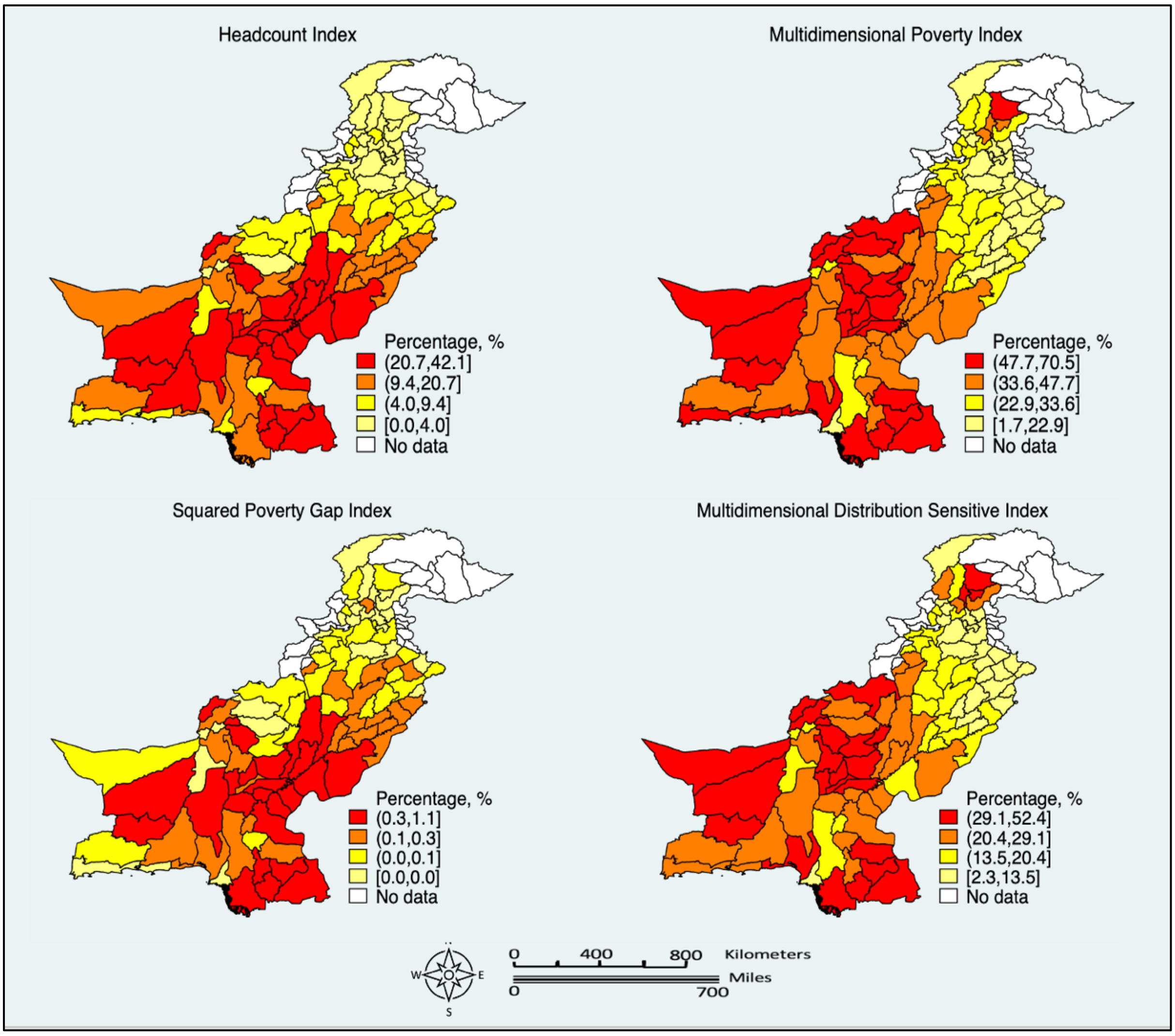
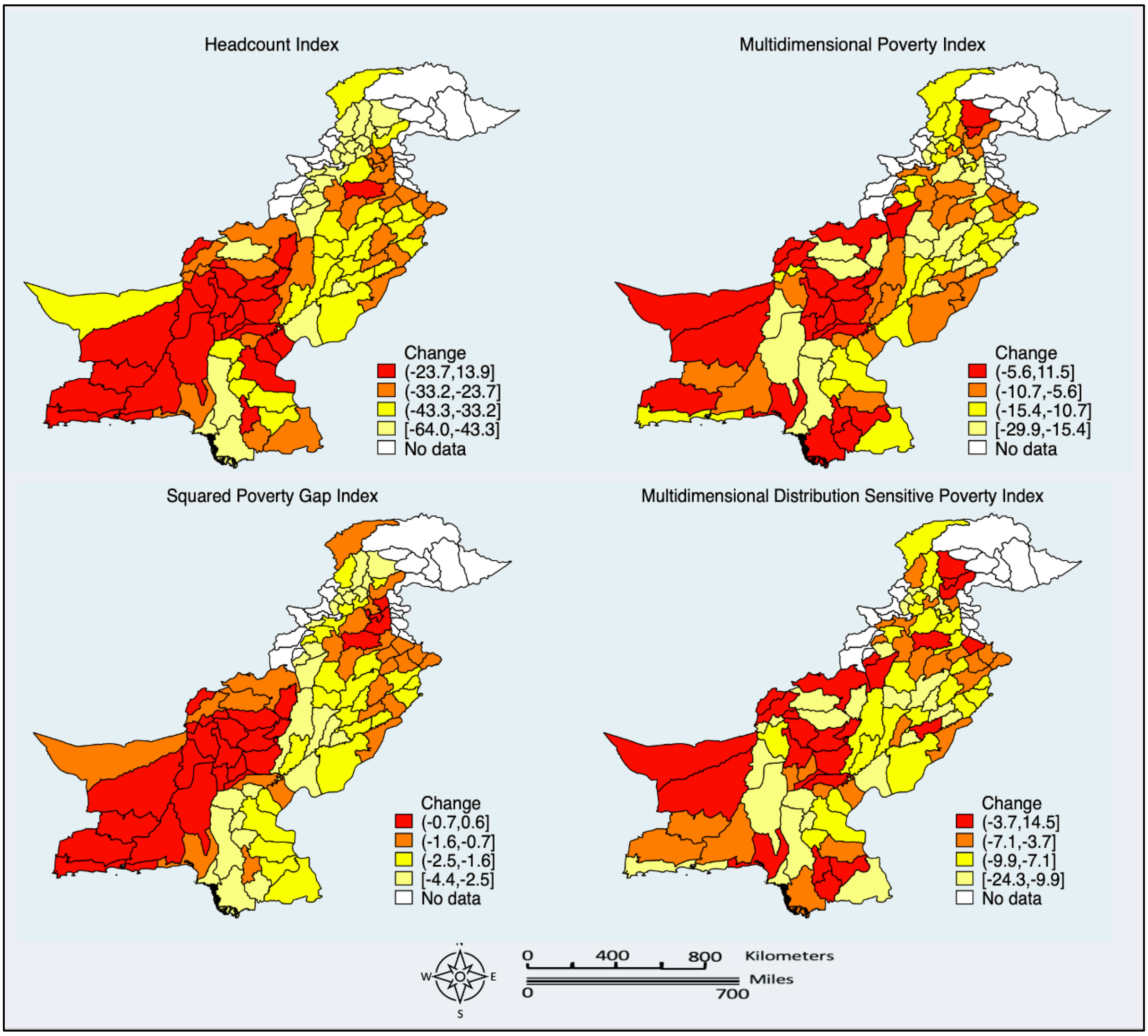


Figure C3: Change in rural poverty estimates of the districts (2014 – 2004)



Appendix D

Table D1: SARAR Model Results for effects of urban growth on rural poverty in Pakistan: 2004-14 (Town luminosity threshold 30%)

	Poverty Indicator			
Variables	HH	SPG	MPI	MDPI
Big city lit area	-0.264	0.396	-0.107	0.146
	-1.27	(2.32)**	-0.74	-1
Big city average DN value	-0.215	-0.035	0.172	0.246
	-1.56	-0.31	(1.74)*	(2.47)**
Secondary town lit area	0.414	-0.418	0.16	0.019
	-1	-1.22	-0.56	-0.07
Secondary town average DN value	-0.449	0.323	-0.165	-0.095
	-1.32	-1.15	-0.7	-0.39
W × Big city lit area	-0.047	-0.025	-0.022	-0.029
	-1.31	-0.86	-1.26	(1.69)*
W × Big city average DN value	-0.024	-0.016	0.022	0.002
	-0.62	-0.52	-1.28	-0.13
W × Secondary town lit area	0.28	0.143	0.167	0.161
	-1.26	-0.77	-1.2	-1.17
W × Secondary town average DN value	-0.219	-0.07	-0.075	-0.069
	-1.17	-0.45	-0.64	-0.6
Spatial lag of poverty rate	-0.046	-0.039	-0.033	-0.037
	(2.15)**	(2.09)**	-1.16	-1.21
Spatial lag of errors	0.147	0.156	0.107	0.093
	(19.38)***	(32.67)***	(5.81)***	(4.34)***
Pseudo-R^2	0.341	0.450	0.009	0.003
Test that spatial lags of indep variables = 0	3.11	2.06	6.73	5.82

Notes: The four poverty variables are HH (headcount index), SPG (squared poverty gap index), MPI (multidimensional poverty index) and MDPI (multidimensional distributionally sensitive poverty index). Secondary towns are defined according to a 20% luminosity threshold. Each regression includes fixed effects for 100 districts and for six years. All variables are in logarithms (using the inverse hyperbolic sine transformation to deal with zeros) and standardized. The test for the spatial lags of independent variables=0 is distributed as chi-squared (4 df). Statistical significance of coefficients is based on z-tests in ( ) with ***, **, * denoting significance at 1%, 5% and 10% levels.

Table D2: Spatial Autocorrelation Model of Effects of Urban Growth on Rural Poverty in Pakistan: 2004-14 (Town luminosity threshold 30%)

	Poverty Indicator			
Variables	HH	SPG	MPI	MDPI
Big city lit area	-0.301	0.399	-0.149	0.07
	-1.47	(2.32)**	-1.12	-0.52
Big city average DN value	-0.245	-0.034	0.2	0.231
	(1.85)*	-0.3	(2.35)**	(2.70)***
Secondary town lit area	0.093	-0.689	0.023	-0.117
	-0.26	(2.63)***	-0.08	-0.4
Secondary town average DN value	-0.215	0.476	-0.124	-0.056
	-0.73	(2.18)**	-0.53	-0.23
Spatial lag of poverty rate	-0.029	-0.065	0.005	0.001
	(1.87)*	(5.82)***	-0.18	-0.02
Spatial lag of errors	0.143	0.197	0.082	0.068
	(20.05)***	(177.62)***	(3.46)***	(2.54)**
Pseudo-R^2	0.400	0.431	0.260	0.212

Notes: see Table D1

Table D3: Spatial Error Models of Effects of Urban Growth on Rural Poverty in Pakistan: 2004-14 (Town luminosity threshold 30%)

	Poverty Indicator			
Variables	HH	SPG	MPI	MDPI
Big city lit area	-0.313	0.4	-0.146	0.07
	-1.53	(2.26)**	-1.09	-0.54
Big city average DN value	-0.233	-0.007	0.204	0.231
	(1.78)*	-0.06	(2.44)**	(2.84)***
Secondary town lit area	0.185	-0.619	0.012	-0.118
	-0.52	(2.26)**	-0.04	-0.42
Secondary town average DN value	-0.291	0.418	-0.115	-0.054
	-0.98	(1.83)*	-0.51	-0.23
Spatial lag of errors	0.134	0.186	0.086	0.068
	(20.70)***	(133.65)***	(7.89)***	(5.75)***
Pseudo-R^2	0.400	0.437	0.260	0.212

Notes: See Table D1

CHAPTER 7[22]

Does the impact of cash transfers differ across poverty measures? Evidence from Pakistan

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[22] It is a University of Waikato working paper

Abstract

Cash transfers have been increasingly used in developing countries as key elements of social protection and poverty reduction strategies. Pakistan is no exception. In 2008, Pakistan introduced the Benazir Income Support Program (BISP) as an unconditional cash transfer targeted at the poorest of the poor. In this paper, I use five poverty measures, calculated biennially from 2008 to 2014 for 100 districts in Pakistan to assess the effectiveness of the BISP in alleviating poverty. I also examine whether the impact of the cash transfer programs on poverty is sensitive to the choice of poverty measure. Our results show that BISP is associated with poverty reduction using either the conventional money-metric poverty measures or multidimensional poverty measures, however the impact is much larger for the conventional poverty measures, which are distributionally insensitive. The implication is that public policy analysts should be cautious in the conclusions they draw from poverty estimate when evaluating welfare programs.

Keywords: poverty, cash transfers, multidimensional, social protection, Pakistan

JEL Classification: I32, I38

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7.1 Introduction

The experience of countries that succeeded in reducing poverty significantly indicates the importance of sustained high economic growth in achieving this result. However, Ravallion (2001) and Fosu (2011) pointed out that high growth alone is not sufficient for poverty alleviation as the very poor are unlikely to benefit from any trickle-down effect that may result from growth. The challenge for policy makers is thus to combine growth-enhancing policies with the right poverty alleviation policies to create opportunities for the poor so that they can contribute to and benefit from growth (Ravallion, 2004). Consequently, in countries where growth is inadequate or is not pro-poor, there is a need to have well-functioning social safety nets to dissipate the increasing income inequality resulting after the spur in growth (Lee and Park, 2002).

There is growing evidence which shows that social safety net programs play a crucial role in reducing poverty and food insecurity. For instance, Devereux (2002) found that the inclusion of cash transfers in social safety net program in Namibia, Mozambique and Zambia reduce chronic poverty. A study by Acasto and Velarde (2015) show that Phillipines' cash transfer program, the *Pantawid Pamilyang Pilipino Progam* (4Ps) has led to a reduction in food poverty and total poverty among beneficiaries by about 7 percentage points. In India, social safety nets also have a significant impact in improving food security (Pritchard et al., 2013). Using data from 142 countries, the World Bank (2018) *State of the Social Safety Nets* report showed that social protection programs cover 56 percent of the poorest population globally and about 36 percent of the very poor who received safety net benefits escaped extreme poverty because of social safety nets. Data from the report also show that safety nets which include unconditional and conditional cash transfers, food and in-kind transfers, public works, school feeding programmes and fee waivers targeted to poor and vulnerable households also lower inequality and reduce the poverty gap by 45 percent.

Safety nets program not only contribute to poverty reduction, but also allow recipients to boost investment in human and physical capital, to smooth consumption and to engage in more risky but productive activities. Numerous impact evaluation studies on conditional cash transfer program *Progresa*[23] in Mexico have shown a substantial improvement in schooling attendance (Schultz, 2004; Attanasio et al., 2011) and other benefits including a 20 percent increase in households' monthly savings (Harrison, 2019) and a significant improvement in the health of both children and adults (Gertler and Boyce, 2003). Existing evidence on the impact of unconditional cash transfers to vulnerable households in Africa also suggest positive effects on the education and health outcomes of children in beneficiary households (Haushofer and Shapiro 2016; Kremer et al 2013). In Kenya, a year-long randomised trial of Give Directly found that the programme's unconditional cash transfers raised psychological wellbeing and food security (Haushofer and Shapiro, 2016). Findings from Uganda show that beneficiary households reported higher consumption expenditure and used part of the cash transfers on health and education related expenditures and investment in productive assets (Merttens et al. 2016).

Despite the wealth of interest from policy makers and researchers, there are a few reasons why the evidence of the impact of social safety nets on poverty and other socio-economic outcomes

[23] Later known as *Oportunidades* and now *Prospera*

is insufficient. First, the evidence is for traditional, money-metric poverty measures, such as the headcount index (the share of the population living in households whose consumption or income is below the poverty line) and the poverty gap index (the average proportionate shortfall from the poverty line). Yet many developing countries are switching to multidimensional poverty measures to either supplement or replace the traditional money-metric ones (Alkire et al., 2015). Secondly, existing studies that investigated the living standards enhancing aspect of social safety nets only use one specific indicator such as school enrolment or health status. Empirical work has shown that significant percentages of those who are multidimensionally deprived are not monetary poor and vice versa (Alkire and Jahan, 2018). As such, it is thus crucial to understand the poverty-reduction impact of social protection programs in a multidimensional framework. Furthermore, to date, no studies compare the impact of social programs in multidimensional measures versus in money-metric measures. And this analysis is important because the study done on Pakistan revealed that spatial patterns and temporal changes appear to be sensitive to using multidimensional versus money-metric poverty measures (Najam, 2020).

In 2008, the government of Pakistan (GoP) launched the Benazir Income Support Program (BISP) to minimize the impact of adverse economic shocks and inflation faced by the poor. The BISP is unique case in social protection for several reasons. First, it is an unconditional transfer. Whereas there is evidence that conditions matter for some outcomes (de Brauw and Hoddinott, 2011), more recent papers that have randomized conditionality find that conditions do not affect impacts on all outcomes (Akresh et al., 2013). Second, the BISP is a nationwide program that has expanded quickly – its coverage has increased from 1.7 million beneficiaries in 2008 to 5.3 million in 2016, and it is expected to reach about 8 million beneficiaries by the end of 2019 (World Bank, 2018). These facts provide an ideal setting to explore whether BISP really target the poor areas. There is also a significant timing issue that is especially relevant in the context of Pakistan. Pakistan has made significant progress in reducing its poverty headcount by nearly 66 percent between 2002 – 2016 during this time its economic performance has been erratic with spurts of high growth periods followed by steep decline, indicating that there is no established relationship between poverty and macroeconomic performance in Pakistan (World Bank, 2016, Afzal et al., 2019). In a recent paper, Najam (2020) reported that while monetary poverty has fallen substantially (from 48.1 percent in 2008, to 13.2 in 2014), improvements in non-monetary social indicators remain sluggish, with the multidimensional poverty index falling from 25.7 in 2008 to 22.1 percent in 2014. Why a mediocre economic growth translated to a significant income poverty reduction but not so much on other social indicators has been puzzling. The apparent disconnect between economic growth and the reduction in poverty leads to the question of what policies have contributed to the decline of poverty in Pakistan. Whether the change in poverty numbers is the result of the cash transfers or the result of economic development initiatives is imperative to the research.

In this paper, I am investigating whether the impact of the BISP unconditional cash transfers program on poverty in Pakistan depends on the type of poverty measure used. I use five poverty measures (two multidimensional and three money-metric and one measure from each of these groups is distributionally sensitive), calculated biennially from 2008 to 2014 for 100 districts in Pakistan. With these multitude of measures, I can assess whether choice of poverty measure matters when assessing the impact of social protection programs. Given that I am using data from ex-post perspective in evaluating the effectiveness of BISP on poverty, I use a quasi-experimental approach and employ the Blinder-Oaxaca decomposition method. To the best of my knowledge, this is the first study that examined the poverty eradicating aspect of social safety nets using both the multidimensional and money metric poverty measures.

The rest of the paper is organised as follows. In section 2, I describe the BISP program and briefly discuss existing studies that look at the impact of BISP in Pakistan. Section 3 provide details on poverty in Pakistan, followed by discussion on data and estimation methodology. Section 5 provides the results and Section 6 concludes the discussion with policy implications.

7.2 An Overview of the Benazir Income Support Programme (BISP)

Pakistan initially developed a Social Protection Strategy in 2007 and then announced the BISP to be its main social safety net program in 2008. The BISP initially aimed to help the poorest of the poor through unconditional cash transfers. It has three main policy goals which include (i) to eradicate extreme and chronic poverty, (ii) to empower women and (iii) to achieve universal primary education (Afzal et al., 2019).

As the Pakistani economy was characterized by high food price inflation when the BISP began in 2008, with its annual inflation rate hitting 21%, up from 12% the year before, there was urgency to increase the declining purchasing power among the poorest members of society. Consequentially, initial program targeting took place through parliamentarians, who were each asked to identify 8,000 beneficiary households on a prescribed form, on which names and household income information were collected. Under this system of community-based targeting (CBT) through politicians, the initial rollout led to disbursement to over 2 million eligible families (Cheema et al., 2015)

As a result of concerns over the effectiveness and transparency of parliamentarian targeting, a new national targeting mechanism based on Proxy Means Test (PMT) was developed. Weights for the PMT were developed using the 2007-08 Pakistan Living Standards Measurement Survey (PSLM). The PMT is based on 23 variables, which include socio-economic characteristics such as household size, housing type, access to sanitation, educational status, household assets, agricultural landholding and livestock ownership. The PMT procedure estimates the welfare status of a household on a scale of 0 to 100 helping in identifying the poorest households. For the application of the PMT formula, a nationwide Poverty Scorecard Survey was conducted in 2010 covering around 27 million households in the country. A PMT threshold (cut-off score) of 16.17 was used to determine the eligibility of the household for unconditional cash transfer[24]. Among the surveyed households, over 7 million (around 28 percent) households across Pakistan were eligible for the unconditional cash transfer, in which 5.8 million families were active beneficiaries up until 2018 (Iqbal and Nawaz, 2019). The breakdown of surveyed households and the eligible households by four provinces, namely Punjab, Sindh, Kyber Pakhtunkhwa (KPK) and Balochistan along with the three federally administrated territories: Azad Jammu and Kashmir (AJK), Gilgit-Baltistan (GB), and Federally Administered Tribal Areas (FATA), is presented in Table 1. The Poverty Score Card (PSC) Survey covered at least about 80 percent of the population in each of these provinces and territories. Proportion of eligible beneficiary households was highest in FATA (52.5 percent), followed by *Balochistan* and *Sindh* (40 percent).

[24] BISP chose a 16.17 cut off score keeping in view the budget availability and proposed amount of monthly stipend (Cheema et al., 2015)

Table 1: Area wise coverage under poverty scorecard survey, 2010

Province	No. of Districts	Estimated Population (in million)	Population Surveyed (in million)	Population Surveyed (%)	HHs Surveyed (in million)	Eligible HHs (in million)	Eligible HHs (%)
Punjab	39	94.36	81.18	86.26	14.88	2.79	18.7
Sindh	27	38.92	34.29	88.11	6.60	2.68	40.1
KPK	24	26.93	21.30	79.09	3.64	1.40	38.5
Balochistan	30	7.62	6.05	79.40	1.10	0.45	40.1
AJK	10	3.87	3.54	88.53	0.58	0.12	20.6
GB	7	1.27	1.13	89.44	0.15	0.05	33.0
FATA	7	3.69	3.06	82.95	0.40	0.21	52.5
Total	**144**	**177.94**	**150.55**	**84.61**	**27.35**	**7.70**	**28.15**

Source: Benazir Income Support Programme (n.d.)

Since the inception, BISP's annual disbursement under the unconditional cash transfer programme increased from Rs. 15 billion in 2008 to Rs. 116 billion in 2018 (see Table 2). Up until 2012 the beneficiary households received Rs 1,000 (around US $10) per month which increased to Rs. 1,200 in 2013, Rs 1,500 in 2014, Rs 1,567 in 2015 and finally to Rs 1,611 in 2016. The amount paid to the beneficiary is around 20% of the monthly income of a daily-wage worker and around 10% of minimum wage set by the government of an unskilled labourer (Saleem, 2019). In the span of 10 years, the BISP's releases as a percentage of GDP increased from 0.1% to 0.35%.

Table 2: Yearly BISP releases and number of beneficiaries

Fiscal Years	Total Yearly Releases Rs. Billion	Releases as % of Federal Revenues	Releases as % of GDP (MP)	Yearly Beneficiaries (Nos. in Millions)	Project Phases**	Cash Amount Per Month Per Beneficiary (in Pak Rupees)
2008-09	15.32	1.3%	0.10%	1.76	Phase I	1,000
2009-10	39.94	3.0%	0.19%	2.58	Phase I	1,000
2010-11	34.42	2.2%	0.19%	3.10	Phase I	1,000
2011-12	49.53	2.6%	0.25%	3.68	Phase I & II	1,000
2012-13	50.10	2.6%	0.22%	3.75	Phase II	1,000
2013-14	69.62	3.1%	0.28%	4.64	Phase II	1,200
2014-15	91.78	3.5%	0.33%	5.05	Phase II	1,500
2015-16	102.00	3.3%	0.35%	5.21	Phase II	1,567
2016-17	111.50	3.3%	0.35%	5.46	Phase II	1,611
2017-18	107.00	3.0%	0.35%	5.63	Phase II	1,611
2018-19	116.50	3.0%	0.35%	5.78	Phase II	1,611

Source: Economic Survey of Pakistan 2017-18

Note: ** Phase I of the project was the Community-based targeting, through parliamentarians while Phase II was targeting through Poverty Score Card

For any social safety net program to be successful, the issue of targeting is of utmost importance. Targeting must be cost-effective and be useable by policy makers in a way that can be used to generate lists of potential beneficiaries. Moreover, procedures must be put in place to ensure that the selection of beneficiary is objective, transparent and consistent across geographical areas (Grosh et al., 2008). As mentioned earlier, BISP adopted two different targeting methods to reach out to the poorest of the poor in Pakistan. In the initial phase, which lasted from 2008 to 2011, the beneficiaries of the program were selected through parliamentarians and their political leaders at the local level, which is akin to Community-Based Targeting (CBT) with an extra layer of being political. In the second phase of the program, the BSIP has been targeted using a Proxy Means Test (PMT) since 2011. While the move to the PMT targeting is perceived to be better than CBT as it limits the biases and rentseeking behaviour of local elites and other community members, the PMT targeting has both inclusion and exclusion errors (Kidd and Wylde 2011).

While designing the PMT, the World Bank (2009) carried out simulation exercises and showed that if the poorest 20% of the population is set as the target group for the BISP, then the leakage rate is expected to be 40% whereas under-coverage rate is expected to be 61%. This implies that 61% of the poor (the poorest 20% of the population) will be excluded from the benefits while 40% of the beneficiaries are non-poor. There are few case studies like Gazdar and Zuberi (2014) and Saleem (2019) which highlighted the exclusion of households which should have been in the eligible household list. This exclusion error along with transition of the targeting methodology in the last 10 years made it important to examine how effective BISP was in reducing poverty over time under its two different targeting phases.

To examine targeting efficiency, I report the percentage of households who are eligible for the BISP, according to the 2010 PSC Survey. This benchmark is then compared to the percentage of poor households according to either the conventional monetary poverty measure or the multidimensional poverty measures (see Table 3). According to the PSC Survey, 28% of households nationally are beneficiaries of BISP, yet the MPI poverty measures suggest that 46 percent of households are poor. Thus, according to this comparison, there is an under-coverage in targeting of about 64%. The gap is even bigger if I use the distributionally sensitive multidimensional poverty measure MDPI developed by Datt (2019), where 89% of households are considered poor. In contrast, when the comparison is made between the PSC eligible households and those who are considered poor under the conventional headcount poverty index, there seems to be over-coverage with the BISP as it has a higher share of households who are eligible than are counted as poor with the headcount index. This evidence indicates there is a need to investigate how effective BISP is in the presence of these discrepancies in the eligibility of poor households.

Table 3: Percentage of eligible households under the 2010 PSC and poor households using conventional, MPI and MDPI for 2010

Provinces	PSC Eligible Household	Conventional Poverty Measure Poor Households*	MPI Poor Households*	MDPI Poor Households*
Punjab	18.7%	18.9%	40.3%	90.7%
Sindh	40.1%	21.9%	45.7%	80.3%
Balochistan	40.1%	11.8%	78.5%	98.0%
KPK	38.5%	20.7%	57.3%	95.6%
National	**27.9%**	**19.5%**	**45.7%**	**89.3%**

Notes: * authors calculation based on Najam (2020)

The impacts of BISP have been studied in several papers, including Pasha et al. (2018) who observed stability in social status of beneficiaries and increase in their consumption of Thatta district of Sindh province as a result of BISP. Junaid and Mohsin (2017) in their research on two districts from Sindh province showed that a total of 105 out of 263 beneficiaries escaped from poverty after BISP. Amrin and Ashfaq (2020) in their research on a city in *Punjab* province found that BISP increases the food expenditure of beneficiaries. Afzal et al. (2019) in their work showed the positive impact of BISP on headcount index. Azeem et al., (2019) in their extensive study on Pakistan for 2010-11 showed the poverty reducing impacts of social protection programmes. Nayab and Farooq (2014) studies the impact of BISP on food and health expenditures. The detailed evaluation conducted by Oxford Policy Management (OPM) on BISP suggests around 3-7 percent reduction in poverty and this range of reduction depends on the poverty line used (Cheema et al., 2015).

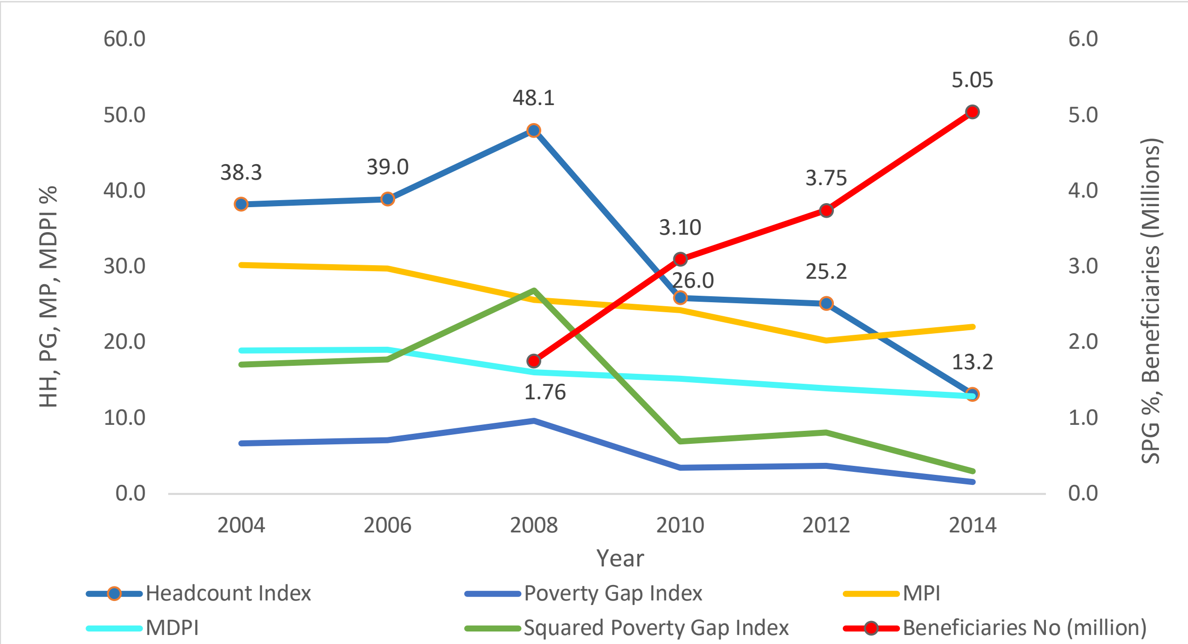
All of the papers mentioned above used money-metric poverty measure to gauge the impact of the BISP. Furthermore, studies that look at the impact of BISP on poverty only concentrated at a rather limited geographical scale. Our paper differs from existing study in the following ways. First, I use poverty estimates for all districts in Pakistan to examine the impact of the BISP. Due to the spatial heterogeneity in terms of economic development between provinces and districts as pointed out in Najam (2020), it is important to look at the effects of the social program at the disaggregated level of Pakistan. Second, I use both money metric and multidimensional poverty measures to analyse the contribution of BISP in reducing poverty. BISP beneficiaries have been criticised for spending their money on supporting their consumption then improving their human capital (Junaid & Mohsin 2017). Analysing the effect of BISP on multidimensional poverty measures can provide some evidence on spending priorities of the beneficiaries.

7.3 Poverty in Pakistan: Background and Data

Figure 1 illustrates the evolution of average poverty rates over the six waves of surveys from 2004 to 2014. The three money-metric measures shown in the figure are the headcount index (HH), the poverty gap index (PG) and the squared poverty gap index (SPG). The SPG is a distributionally sensitive measure that puts more weight on the people furthest below the poverty line, while HH and PG are not distributionally sensitive. The other two measures are the MPI, which is based on Alkire and Foster (2011) and Alkire et al. (2015), and the multidimensional distribution-sensitive poverty index (MDPI) developed by Datt (2019). As the name implies, the MDPI is distributionally sensitive while the MPI is not. The detailed formulae for these five indices are provided in Appendix A, with full details on the survey data used to construct them in Najam (2020). For money-metric poverty measures, this involves Elbers et al. (2003) approach to project consumption data from the Household Income and Expenditure Survey (HIES) onto the sample of the Pakistan Social and Living Standard Measurement Surveys (PSLM) that lacks consumption data, using sets of predictor variables from the two surveys that overlap. PLSM surveys are representative at district-level, and are used to directly calculate the multidimensional poverty measures. This survey-to-survey imputation approach provides district-level money-metric poverty estimates. Full details are available in Najam (2020). For our purposes here, it is sufficient to note that I have estimates at the district level for every second year, from 2004 to 2014.

According to Figure 1, the headcount poverty rate was around 40% in 2004 and 2006 but rose to almost 50% in 2008 (Figure 1). This sharp increase in poverty is due to the world food price surge in 2008, in which Pakistan's annual inflation increased from 7.7% in 2007 to 21% in 2008. These increases were followed by an even sharper fall, to about 25% in 2010, with a slight decline in 2012 and then a further sharp decline to below 15% by 2014. The movements of the poverty gap index were even more pronounced, rising faster from 2006 to 2008 and then declining even faster than what the movements in headcount poverty index show. The patterns for SPG are similar but with less sharp movements, so the overall patterns revealed by the money-metric measures is that poverty rates in 2014 were substantially lower than in 2004, albeit with an initial period of rising poverty, especially in 2008.

Figure 1: Average poverty estimates (District-level) for six alternative years (2004 2014) and number of BISP beneficiaries



Source: Najam (2020)

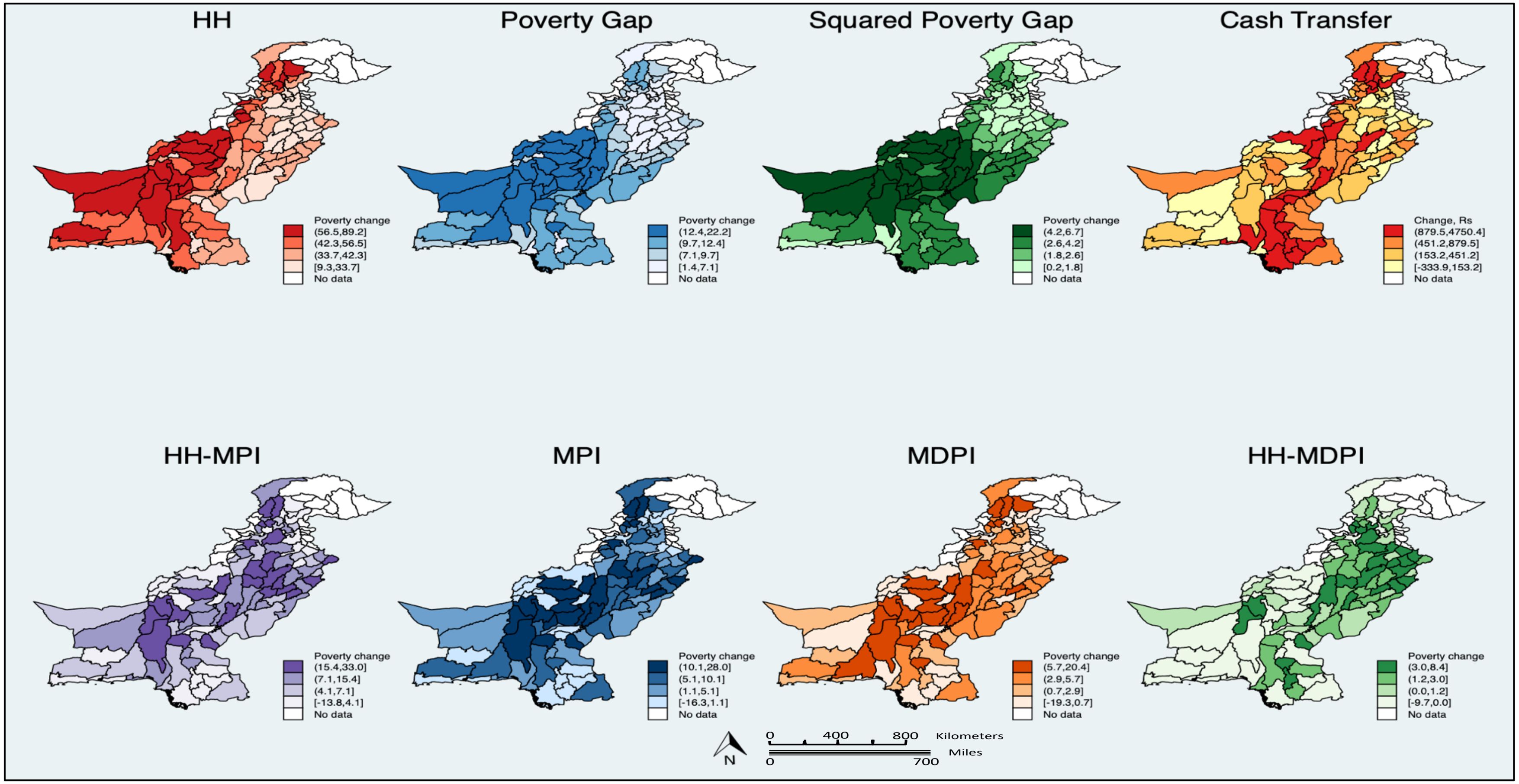
The multidimensional poverty measures present quite a different picture. There was a slow decline in the MPI, with an average index value of about 30% in 2004 declining to be just above 20% by 2014. The average level of the MDPI starts lower but does not decline quite as fast and neither measure shows any jump in 2008, unlike the fluctuations seen with the money-metric measures. The trends shown in Figure 1 relate to averages over all 100 districts (for 6 years) but a disaggregated analysis by Najam (2020) also shows that the time trends in poverty in Pakistan depend on what sort of measures are used; over two-thirds of the districts show opposite trends in poverty rates, if using multidimensional measures rather than money-metric ones, for at least two of the five spells between the six survey waves. Figure 1 also shows that number of the BISP has increased substantially from 1.76 million in 2008 to 5.1 million beneficiaries in 2014.

To capture spatial heterogeneity within the country, in Figure 2, I present district-level maps of the change in the poverty rates over the 2008 to 2014 period for the five poverty measures and coverage of the BISP cash transfer. The darker colours on the map denote districts that had the fastest rates of poverty reduction. There are also some districts with no data, mainly in the Federally Administered Tribal Areas (FATA), where the PSLM surveys were not fielded due to the security situation. A group of neighbouring districts in Balochistan province (in the southwest) are among those with the least reduction in money-metric poverty measures over 2008-2014 after having the highest poverty rates in 2008. The larger physical size of some of these districts draws attention to them but it is also the case that the majority of districts with the least poverty reduction are in Balochistan because these were the districts that had highest rates of poverty in 2008.

In contrast to the maps for money-metric poverty measures, where the slowest rates of poverty reduction are mostly in Punjab, Sindh and a few scattered parts of Khyber Pakhtunkhwa, the multidimensional poverty measures show patterns that are more spatially random. The slowest rates of reduction in multidimensional poverty includes parts of Sindh and Balochistan provinces, plus some districts from Khyber Pakhtunkhwa.

In terms of the changes in coverage for the cash transfer, the map shows that majority of districts in Sindh province (in the southeast) and few districts in the Khyber Pakhtunkhwa province are among those with the highest increase in terms of per capita cash transfer between 2008-2014, while there seems to be a reduction in terms of coverage of the BISP in several districts within the Punjab province.

Figure 2: Change in poverty estimates and cash transfer coverage for the districts between 2008 – 2014



Notes: HH, Headcount Index; HH-MPI, Alkire & Foster (2011) Multidimensional Headcount Index; HH-MDPI, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP). Poverty changes are pre-BISP minus post-BISP

7.4 Empirical Methodology

The focus of this study is to investigate the impact of BISP in eradicating money-metric and multidimensional poverty at the district level of Pakistan based on the assumptions of counterfactual reasoning as I am evaluating the impact of social programme which has been implemented. The analysis is done in two stages. In the first stage, I employ the counterfactual decomposition technique introduced by Blinder and Oaxaca to examine: (i) if the same trends in poverty are apparent if one uses either the conventional or the multidimensional measures before and after the implementation of the BISP and (ii) whether the reduction in poverty is due to result of improvement in factors such as infrastructure or due to BISP. In the second stage, the impact of cash transfers in reducing poverty using conventional and non-conventional poverty measures is estimated along with investigating which targeting regime (CBT vs PMT) worked better.

7.4.1 Blinder- Oaxaca Decomposition

The Blinder- Oaxaca Decomposition has been most frequently applied in labour economics to explain wage differentials between groups, such as males and females, immigrants and natives and black and white workers. It decomposes the average difference between two groups into three components. The first component explains the difference between two groups due to differences in their endowments (the covariates in the wage equation). The second component refers to the difference due to different returns to these characteristics (that is, differences in the coefficients of the wage equations). It is this second component that can indicate the presence of gender or racial biases, whereby people with the same characteristics receive different payoffs. The third component is the combination of endowments and coefficients, and is known as the interaction component.

In this paper, I use the Blinder-Oaxaca decomposition method to investigate if there is any significant difference in the average poverty estimates before and after the implementation of the BISP. The decomposition technique allows the identification of how much of mean differences on outcomes across two time periods can be explained by the differences in observed characteristics. The rest of differences that cannot be explained by observed characteristics can be defined as exogenous effects. In this light, the Blinder–Oaxaca decomposition can be applied in policy evaluation to estimate the net policy impact (Hwang and Lee, 2015)

To identify the policy impact of BISP on poverty using the Blinder-Oaxaca decomposition, linear regression defined by equation (1) is divided into two groups: 'pre' BISP and 'post' BSP. In the first equation, the poverty estimates from the first group 'pre', before 2008, are regressed on a set of covariates. In the second equation, the poverty estimates from the second group, 'post', calculated using conventional and non-conventional poverty estimates are regressed on covariates post 2008. The covariates used in both these regressions include household characteristics, access to services and facilities that define the living standard of a household such as electricity, gas, access to water, access to hospitals, schools, number of rooms, brick wall, number of rooms.

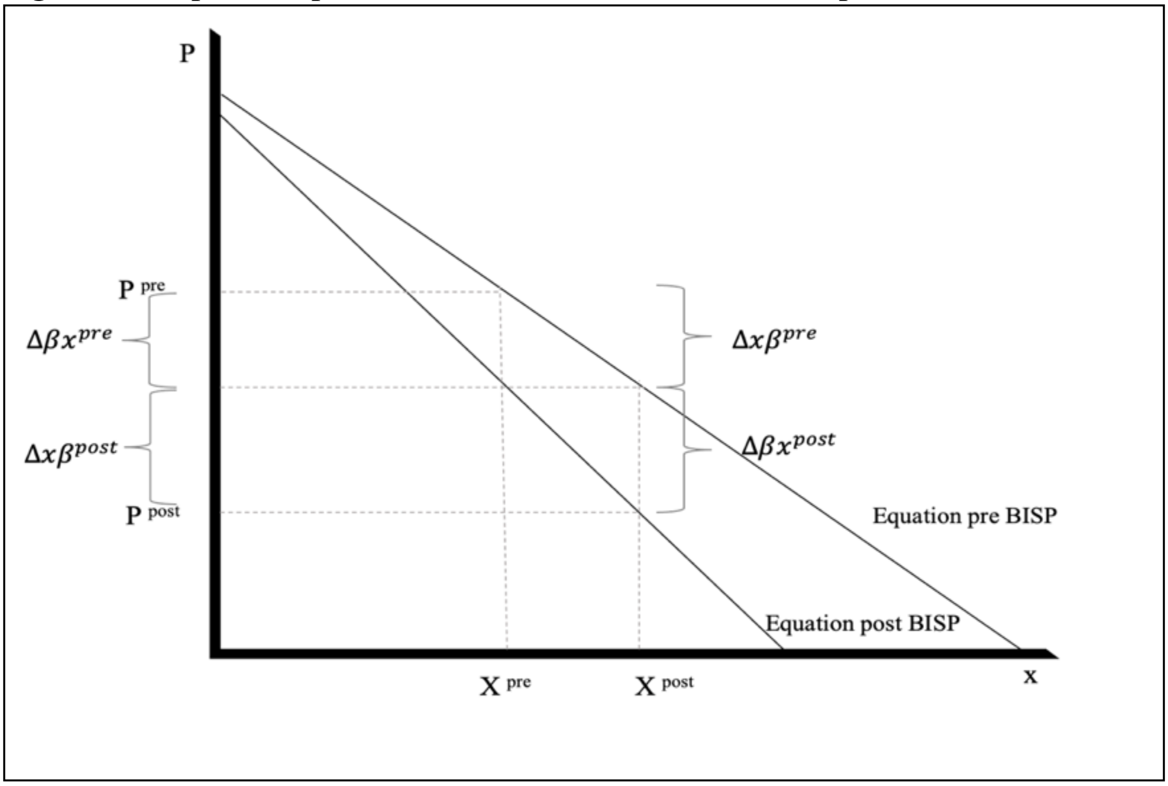
$$P_i = \begin{cases} \beta^{pre} x_i + \varepsilon_i^{pre} & Pre\ BISP \\ \beta^{post} x_i + \varepsilon_i^{post} & Post\ BISP \end{cases} \tag{1}$$

where x_i is the set of covariates, P_i is the money metric and multidimensional poverty estimates. The difference in the average poverty estimates for two groups, pre- and post- BISP can be expressed as:

$$p^{pre} - p^{post} = \beta^{pre} x^{pre} - \beta^{post} x^{post} \quad (2)$$

A simple graphical representation is presented in Figure 3, with poverty as the outcome variable and for simplicity I assume a single covariate, *x,* such as number of rooms, which is negatively associated with poverty; and the mean level of *x* in post-BISP is higher than that of in the pre-BISP because of the improvements in social indicators over time (World Bank, 2016).

Figure 3: Graphical representation of Blinder-Oaxaca decomposition



I assume that the difference in average poverty estimates between two groups is not merely because of the difference in the value of covariates, $\Delta x\beta^{pre}$, but is also due to the difference in effects of those covariates, the slope of the model, $\Delta\beta x^{post}$. The above figure implies the following:

$$p^{pre} - p^{post} = \Delta\beta x^{post} + \Delta x\beta^{pre} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

where,

$$\Delta x = x^{\text{pre}} - x^{\text{post}}$$

$$\Delta\beta = \beta^{\text{pre}} - \beta^{\text{post}}$$

Expanding equation 3 leads to the following equation 4. The derivation is in Appendix B.

$$p^{pre} - p^{post} = (x^{\text{pre}} - x^{\text{post}})\,\beta^{\text{post}} + (\beta^{\text{pre}} - \beta^{\text{post}})\,x^{\text{post}} + (x^{\text{pre}} - x^{\text{post}})\,(\beta^{\text{pre}} - \beta^{\text{post}}) \;\ldots\ldots\ldots (4)$$

Equation (4) shows the threefold decomposition of the average difference in poverty estimates for two groups. The difference $p^{pre} - p^{post}$ is decomposed into three parts: (i) endowments $(x^{\text{pre}} - x^{\text{post}})\,\beta^{\text{post}}$, (ii) coefficients $(\beta^{\text{pre}} - \beta^{\text{post}})\,x^{\text{post}}$ and (iii) interaction $(x^{\text{pre}} - x^{\text{post}})\,(\beta^{\text{pre}} - \beta^{\text{post}})$. Endowments constitute the differences caused due to the change in covariates (x) post- and pre- BISP. Coefficients constitute the difference caused due to factors other than changes in endowment and/or covariates. In our study, because the demarcation between two groups is because of the initiation of a social safety net program, BISP, any difference caused by the coefficient component points towards BISP. The third component, interaction, refers to the difference caused because of the coexistence of endowments and coefficients.

Given the declining trend of poverty estimates for conventional and non-conventional poverty measures (Najam, 2020), I can observe if the reduction in poverty using both conventional and non-conventional poverty measures between 2004-2006 and 2008-2014 is a result of economic development in terms of increased access to services and facilities (i.e. endowments component) or there is an unexplained component to it as well (i.e. coefficients component).

7.4.2 Panel Regressions

Once I have a significant coefficient component from the Blinder-Oaxaca decomposition, I run a panel regression on the period post inception of the BISP in 2008. In the presence of control variables, the panel regression shows how influential the cash transfers are in reducing the poverty estimates generated through money-metric and multidimensional approaches, in which some of them comply to the axiom of distribution sensitivity. As explained earlier, BISP had two targeting phases, from 2008-2010 it relied on CBT and post 2010 it relies on PMT. In our analysis, it is important to observe whether changing the targeting approach has any significant impact in reducing poverty at the district level. I want to observe whether the effect of Cash Transfer (CT) on poverty estimates changes (+/-) when there is a change in the targeting approach. To factor this in, I also included an intercept dummy $(Phase)$ and interactive dummy $(CT_{it}) * (Phase)$. Hausman test is applied to select the appropriate structure of panel model for each poverty measure. Equations 4.1 and 4.2 represent the structural form of fixed effect panel while those for the random effect are shown in equation 4.3 and 4.4.

$$P_{it} = \alpha + \beta(CT_{it}) + \gamma(x_{it}) + \delta(D_i) + \varepsilon_{it} \ldots\ldots\ldots\ldots \quad (4.1)$$

$$P_{it} = \alpha + \beta(CT_{it}) + \gamma(x_{it}) + \eta(Phase) + \delta(D_i) + \theta(CT_{it})(Phase) + \varepsilon_{it} \ldots\ldots \quad (4.2)$$

$$P_{it} = \alpha + \beta(CT_{it}) + \gamma(x_{it}) + \delta(D_i) + U_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots \quad (4.3)$$

$$P_{it} = \alpha + \beta(CT_{it}) + \gamma(x_{it}) + \delta(D_i) + \eta(Phase) + \theta(CT_{it})(Phase) + U_{it} + \varepsilon_{it} \quad (4.4)$$

where

P_{it}= Poverty estimates for district *i* in time *t*

CT_{it} = Cash transfers for district *i* in time *t*

x_{it}= Set of control variables that falls into the broader categories of demographics, education, health, living standards and access facilities

D_i = District dummy in fixed effect model

$Phase$ = Dummy for the change in targeting phase. = 1 if CBT and = 0 if PMT

ε_{it} = Error term

U_{it}= Between districts error term in random effect model

7.5 Results

Prior to analysing the effect of BISP cash transfer on poverty and whether the choice of poverty measure matter, I compared the coverage of the cash transfer at the district level across four alternate years. Appendix C provides spatial profile of both money metric and multidimensional poverty estimates along with the amount of cash transfers at the district level for four alternate survey years of 2008, 2010, 2012 and 2014.

The districts which have the highest poverty estimates whether using conventional or non-conventional poverty measures do not completely fall into the list of districts which received highest per capita cash transfers. Even after 2010 when the targeting approach was changed to PMT, the districts which have the highest incidence of poverty based on money-metric poverty measures (headcount) are not falling into the highest cash receiving tier. If I consider the headcount of the multidimensional poverty estimates, the districts with highest incidence of poverty which are concentrated in the south-west of Pakistan (Balochishtan province) are not receiving the highest amount of cash transfers. BISP does not seem to be targeting districts with highest incidence of poverty even if I just consider the spatial profile using headcount indices. If I consider complex poverty measures which are sensitive to the depth and distribution of the poverty, the coverage of BISP seems even less well targeted.

Although there is poor overlap between the coverage of BISP and the poverty measures, it is important to observe if there is any significant difference in average poverty estimates before and after the start of the largest social safety net program in Pakistan. In particular I want to examine the effects of factors other than changes in household endowments. To examine the drivers of poverty reduction, Table 4 reported Blinder-Oaxaca decomposition for not only money-metric but also multidimensional poverty measures.

For money-metric poverty measures, it showed that there was a relatively large decline in poverty of about 12.33 percentage points for monetary HH poverty measure. Similar magnitude of poverty reduction was observed if using the distributional insensitive multidimensional poverty index MPI (a reduction of 10.21 percentage points). Appendix D provides the Blinder-Oaxaca decomposition results in details.

Table 4: Drivers of poverty reduction: Decomposing changes in poverty

Poverty Measures		Difference	Endowment	Coefficient	Interaction
Money Metric	Distribution Insensitive				
	Headcount Index (HH)	12.33*** (1.82)	5.94 ** (3.02)	5.64 *** (2.08)	0.74 (3.19)
	Poverty Gap Index (PG)	2.85 *** (0.44)	1.0 *** (0.37)	1.72 *** (0.45)	0.13 (0.39)
	Distribution Sensitive				
	Squared Poverty Gap Index (SPG)	0.80 *** (0.13)	0.28 *** (0.10)	0.51 *** (0.14)	0.02 (0.12)
Multidimensional	Distribution Insensitive				
	Multidimensional Poverty Index (MPI)	7.02 *** (1.31)	5.52 *** (1.3)	0.81 (0.63)	0.69 (0.57)
	Headcount MPI	10.21 *** (1.88)	8.04 *** (1.89)	1.06 (0.77)	1.10 (0.69)
	Distribution Sensitive				
	Multidimensional Distribution-sensitive Poverty Index (MDPI)	4.72*** (0.90)	2.58 *** (0.82)	1.13 (0.86)	1.00 (0.81)
	Headcount MDPI	2.03 *** (0.60)	1.55 * (0.43)	0.42 (0.56)	0.05 (0.36)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level. The differences in poverty estimates are pre-BISP minus post-BISP (hence the positive sign of poverty reduction)

For all of our poverty measures irrespective of whether they are money metric or multidimensional or distribution sensitive, they have shown decrease in poverty estimates after the cash transfers. The reduction in poverty is the greatest for the HH (a 12.33 percentage reduction). The statistically significant effect of endowment component indicates the difference in poverty estimates between two periods is because of the difference in endowments that households possess. The development projects and/or initiatives have increased in numbers and in value over time, which is helpful in uplifting the living standards of Pakistani people and ultimately decreasing the level of poverty, represented through endowment component. Various development projects were put in place during these periods, which include construction of degree colleges for girls in different villages and towns, construction of centres in hospital for transplantation and blood transfusions, construction of training and welfare institutes, building of new roads under China-Pakistan Economic Corridor.[25] The development expenditure as percentage of GDP was 3.9 in 2004 which increased to 4.9% by 2014 (Ministry of Finance, 2018). The significant endowment component refers to this development as a source for poverty reduction. However, the significant coefficient component refers to the other unexplained factors beyond endowments. In our case the only factor that is creating two distinct groups is the presence of cash transfers (BISP). The significant coefficient component refers to the part of difference caused because of the cash transfers.

In the case of money metric poverty measures, the reduction in poverty estimates between two time periods is majorly due to the (coefficient) return on endowments which refers to the cash

[25] The details on development projects in Pakistan can be found at https://www.pc.gov.pk/

transfers in our case. Also, the money metric poverty measure, which account for the depth in poverty and distribution sensitivity axiom, is predominately reduced due to the return on endowments (cash transfers). The reduction in money-metric poverty measures over two periods is induced due to both the increase in endowments / services / facilities available to the households and also due to the cash transfers made to the households. Hence, not only the growth and development in the economy is helping households in increasing their consumption but also the cash transferred to the households is providing the support.

In the case of multidimensional poverty measures, the reduction in poverty estimates is caused due to the improvement / increase in endowments. The return on endowment (coefficient) though is positive but is insignificant. The factors other than increased access to services and facilities are not significant in reducing the multidimensional poverty estimates. The results showed that after 2008 when BISP was implemented, the reduction in multidimensional poverty estimates is due to increased / improved access to services and facilities. As the multidimensional poverty measures are based on the access to the services and facilities hence any improvement in those statistics must come from increase in assets, facilities and services available to the individuals. However, an explicit regression modelling has revealed the impact of cash transfers made to the households in uplifting the living standard and human capital of households (World Bank, 2016).

The panel regression run on poverty measures at the district level post 2008 is shown in Table 5 below. Districts in Pakistan belong to different geographical and economic characteristics. For instance, some districts rely on agricultural, while other rely either on tourism as their revenue generating process. To take into account the heterogeneity across districts in Pakistan, I included district fixed effects in the model. The amount paid to the poor households has been revised over years which takes into account the changing economic conditions of the economy. The other covariates that I used control for the development initiatives that affects the access to services and facilities.

The coefficient of log cash transfer from the first model and the coefficients of dummy variables that accounts for different targeting process from the second model (Eq 5.2 and 5.4) for respective poverty measures are presented in Table 5 below. Detailed regression results are given in Appendix E.

Table 5: Panel Regression Cash Transfer Coefficients for Poverty Measures' Models

		Model 1	Model 2		
	Poverty Measures	Log Cash Transfer	Log Cash Transfer	Log Cash Transfer × Phase I	Phase
		Distribution Insensitive			
Money Metric	Headcount Index - HH	-10.8*** (1.38)	-11.25*** (1.59)	-2.16* (1.28)	40.82* (24.43)
	Poverty Gap Index - PG	-1.93 *** (0.34)	-1.79*** (0.39)	-0.98*** (0.32)	18.70*** (6.15)
		Distribution Sensitive			
	Squared Poverty Gap Index - SPG	-0.49 *** (0.10)	-0.44*** (0.12)	-0.30*** (0.09)	5.69*** (0.12)
		Distribution Insensitive			
Multidimensional	Multidimensional Poverty Index - MPI	-0.98 ** (0.01)	-1.58*** (0.42)	1.34*** (0.34)	-24.62*** (6.57)
	Headcount MPI	-0.96 * (0.55)	-1.81** (0.55)	1.79*** (0.45)	-31.47*** (8.52)
		Distribution Sensitive			
	Multidimensional Distribution-sensitive Poverty Index - MDPI	-0.82 *** (0.26)	-1.21*** (0.27)	0.35*** (0.32)	-7.95 (6.10)
	Headcount MDPI	-0.28 * (0.16)	-0.19 (0.19)	0.26 (0.18)	-4.59 (3.44)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

All the poverty measures except MDPI have taken the form of fixed effect panel regression (based on Hausman test results). MDPI which is distribution sensitive has taken the form of random effect panel model. The random effect is plausible when there is influence of entities (districts) on the dependent variable. In our case there is a plausible influence of districts on the distribution sensitive MDPI as Khan and Sasaki (2003) identified the polarisation of development priorities in Pakistan. The development projects are concentrated on certain regions and constituencies, therefore, multidimensional poverty estimates which are distribution sensitive are affected by development status of the districts (Najam, 2020).

Two models are estimated. The second model considers different targeting regimes, which changed from the CBT to PMT after 2010. For both models, cash transfers for money-metric as well as multidimensional poverty measures are shown to have poverty reducing impact. The impact is stronger for conventional poverty measures. In the second model, the dummy variable is included to factor in the switch from the CBT to PMT. The results show that CBT process was stronger in reducing poverty when the poverty is estimated using conventional poverty measures. But if the researchers relied on non-conventional poverty measures they are going to infer that the PMT targeting process was more effective in reducing poverty than the CBT. The reason for the stronger effect of BISP in reducing multidimensional poverty in the second targeting phase is because the Poverty Score Card used for screening and identifying poor households asked questions which are related to assets / services / facilities available to the individuals. Those are the variables used in constructing multidimensional poverty measures. That means if the screening and identification have questions related to consumption or income, it will closely target poor households which would also be identified using money-metric poverty measures.

However, if I just consider the impact of cash transfers in reducing poverty, the impact is significant for money-metric and multidimensional poverty measures except for the Multidimension Distribution-sensitive Poverty Headcount (MDPI). One thing to note here is that the unconditional cash transfers is not just reducing the poverty through increasing consumption but also through uplifting living standards. Dietrich et al. (2020) in their study on Uganda showed that there is positive impact of cash transfers on human capital. In our case, the plausible explanation is that the improved financial conditions help the households to invest in not only human capital but also in other facilities which help in reducing multidimensional poverty estimates. There has been a criticism on the unconditional cash transfer programmes that they fail to provide sustained means of livelihood to the beneficiaries (Molyneux et al., 2016). Multidimensional poverty measures which are calculated using indicators / variables which are responsible to provide sustainable means of likelihood to the individuals have shown improvement after the unconditional cash transfers were made. This analysis helped in putting aside the concern of researchers that unconditional cash transfers does not help in promoting sustainable consumption / investment decisions.

It follows that anti-poverty programmes which involve unconditional financial support to poor families also have an influence on enhancing capabilities of individuals. Multidimensional poverty measures which are developed on capability approach have shown reduction due to increase in cash transfers. There is one more point that needs attention. In this analysis, the distribution sensitive multidimensional poverty measure has taken the random effect form which means that district characteristics could have an influence on MDPI. The polarisation of infrastructure development in certain districts have deteriorated the capabilities set of individuals in deprived districts. Hence, the concentration of high MDPI estimates in less developed districts is observed. Therefore, the depolarisation of development priorities in districts is crucial for increasing the access to services and facilities and for the effects of cash transfers to spread across.

7.6 Conclusions

To ensure that social safety net programs reach the poorest segment of the society, analysis is required to observe how effective those programs are in alleviating poverty over time. Given that there is evidence of poverty trends across time being sensitive to the choice of poverty measure, it is thus necessary to check for the sensitivity of the effect of cash transfers in alleviating poverty calculated through different poverty measures.

In this paper, I use five poverty measures, calculated biennially from 2008 to 2014 for 100 districts in Pakistan to assess the effectiveness of the BISP in alleviating poverty. I also examine whether the impact of the cash transfer programs on poverty is sensitive to the choice of poverty measure. Our results show that poverty reducing effects of BISP is not just on money metric but also on multidimensional poverty measures. However, the effect of BISP is stronger in reducing conventional poverty estimates as compared to the non-conventional poverty estimates. One important thing to conclude from the results is that if I consider the concept of depth, intensity and distribution sensitivity in quantifying poverty, more support in terms of cash transfers is required to eradicate poverty. Our findings also support that households are using the cash transfers not for just supporting consumption, but also in improving their living standards.

Under the current BISP system, a set amount of cash is paid to the eligible households irrespective of how many people are living in the household or how deprived the household is. In order to reach out to the poorest households with the sufficient support, the distribution sensitive poverty measures should be considered in identifying and targeting the households. Increasing the amount of cash transfers on the basis of the depth / intensity of deprivations should be considered by policy makers.

In terms of comparison between the two targeting approaches used, the results showed that CBT was more effective in reducing money-metric poverty estimates whereas PMT was better in reducing multidimensional poverty estimates. It is recommended here that the poverty score card which is used to identify the poor households should at least include some questions on consumption / income in the survey. It is important to add these aspects into the identification survey because from the study by Saleem (2020) on a district in the Khyber Pakhtunkwa Province, there were a few households which were struggling financially and yet did not meet the PMT criterion. Consequently, if a household has basic assets and facilities listed under Poverty Score Card but is struggling to meet its ends, it will not make the eligibility criterion. The point to consider is that the households which are only financially constrained but are doing better in terms of access to services and facilities may not be eligible for the BISP payments because they are evaluated on a totally different criterion which only consider assets, access to services and facilities but not consumption. In Pakistan, it is difficult to sell the assets to meet the consumption needs so even if a household has assets they might not be able to meet their consumption needs in short run. Whereas the Poverty Score Card surveys just captures deprivation in access to services and facilities not consumption.

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Appendix A

Table A1: Description of the five poverty measures used in the study

Poverty Measures	Description
Money-Metric	
Distribution Insensitive	
Headcount Index: $HH = (q/n) \times 100$	where q is the number of poor people living below the poverty line and n is the total number of people. HH is the proportion of people living below the
Poverty Gap Index: $PG = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z-Y_i}{Z}\right)\right)}{n} \times 100$	where Z is the poverty line and Y_i is individual i's consumption. PG measures the intensity of poverty in a given society
Distribution Sensitive	
Squared Poverty Gap: $SPG = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z-Y_i}{Z}\right)^2\right)}{n} \times 100$	where Z is the poverty line and Y_i is individual i's consumption. SPG averages the squares of poverty gaps relative to the poverty line and it gives heavier weight than the PG to the poverty
Multidimensional	
Distribution Insensitive	
Multidimensional Poverty Index $MPI = \mathrm{M}(\alpha, \mathrm{k}; \mathrm{y}) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right) I_i^k \times 100$	For n individuals and d total dimensions, $g_{ij}^{\alpha} = (1 - y_{ij}/z_j)^{\alpha} I_{ij}$ for $\alpha \geq 0$ is the indicator for deprivation for an individual i in dimension j. z_j is the cut-off point for the dimension j. $I_i^k = I(C_i \geq k)$ is the poverty indicator in which k is the cut-off number of dimensions in which an individual has to be deprived to be poor and C_i is the total dimensions in which an individual
Distribution Sensitive	
Multidimensional Distribution-Sensitive Poverty Index $\mathrm{MDPI} = \mathrm{M}(\alpha, \beta; \mathrm{y}) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right)^{\beta} \times 100$	For $\beta > 1$, the measure M(α, β; y) satisfies the cross-dimensional convexity axiom, where: $g_{ij}^{\alpha} = (1 - y_{ij}/z_j)^{\alpha} I_{ij}$ for $\alpha \geq 0$ and y_{ij} is the individual i's score in dimension j and z_j is the cutoff point for deprivation j. $I_{ij} = I(y_{ij} < Z_j)$ 0 – 1 deprivation indicator function and I_{ij} takes value of

Appendix B

Blinder-Oaxaca Decomposition Derivation

$p^{pre} - p^{post} = \beta^{pre}x^{pre} - \beta^{post}x^{post}$ ……………………………………………..……1

Add and subtract the following from the equation 1

$\beta^{post}x^{post}$
$\beta^{pre}x^{post}$
$\beta^{post}x^{pre}$

Resulting into equation 2

$p^{pre} - p^{post} = \beta^{pre}x^{pre} - \beta^{post}x^{post} + (\beta^{post}x^{post} - \beta^{post}x^{post}) + (\beta^{pre}x^{post} - \beta^{pre}x^{post}) + (\beta^{post}x^{pre} - \beta^{post}x^{pre})$ ………………………………………….…..…..2

Rearrange the equation 2

$p^{pre} - p^{post} = (x^{\text{pre}} - x^{\text{post}})\, \beta^{\text{post}} + (\beta^{\text{pre}} - \beta^{\text{post}})\, x^{\text{post}} + (x^{\text{pre}} - x^{\text{post}})\, (\beta^{\text{pre}} - \beta^{\text{post}})$……….3

The equation 3 can be written as follows
$p^{pre} - p^{post} = \Delta x\beta^{post} + \Delta\beta x^{post} + (x^{\text{pre}} - x^{\text{post}})\, (\beta^{\text{pre}} - \beta^{\text{post}})$ ……………..……………4

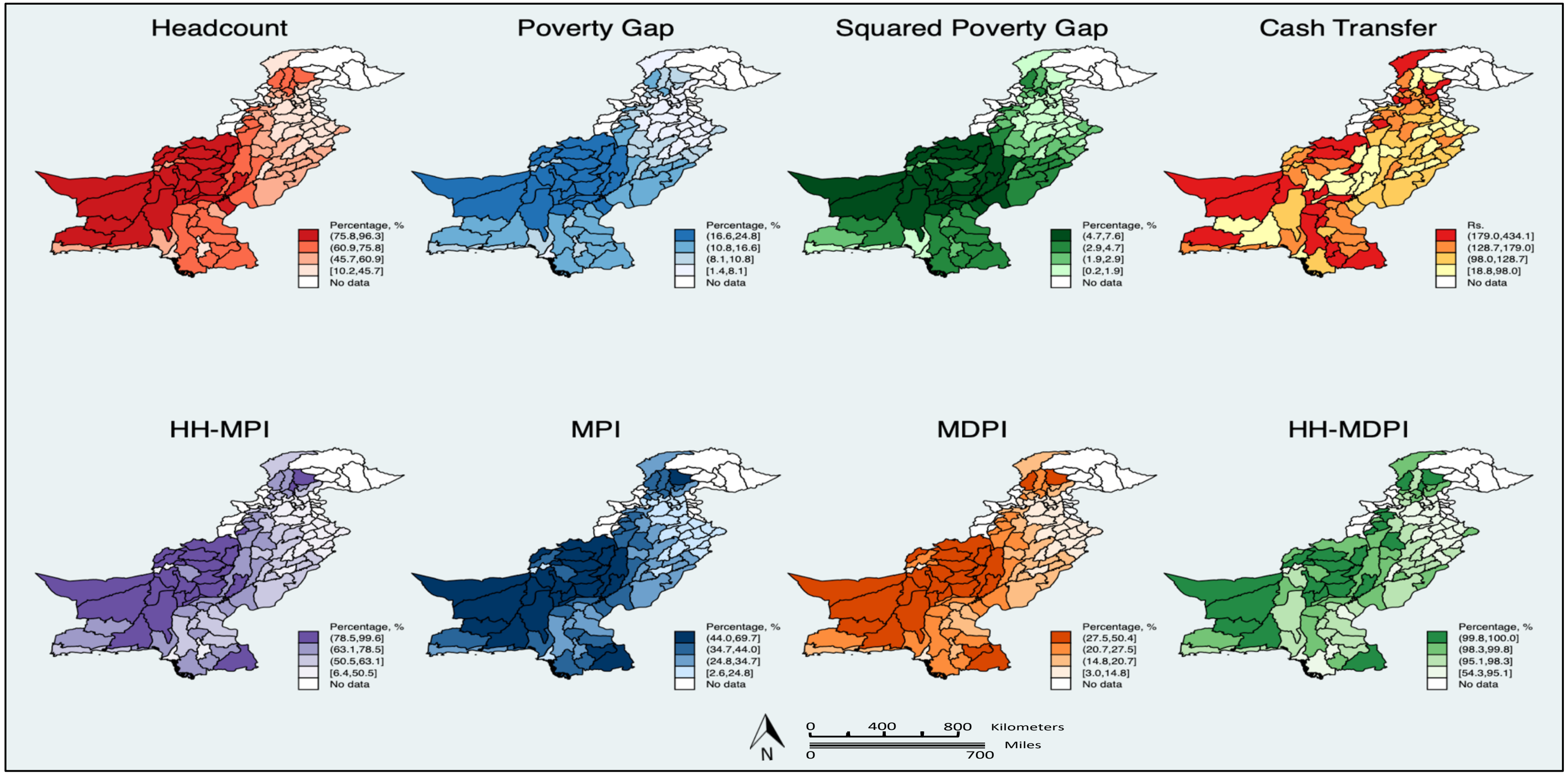
Whereas;

$\Delta x = x^{\text{pre}} - x^{\text{post}}$
$\Delta\beta = \beta^{\text{pre}} - \beta^{\text{post}}$

The following are the three decomposed components from Blinder-Oaxaca decomposition

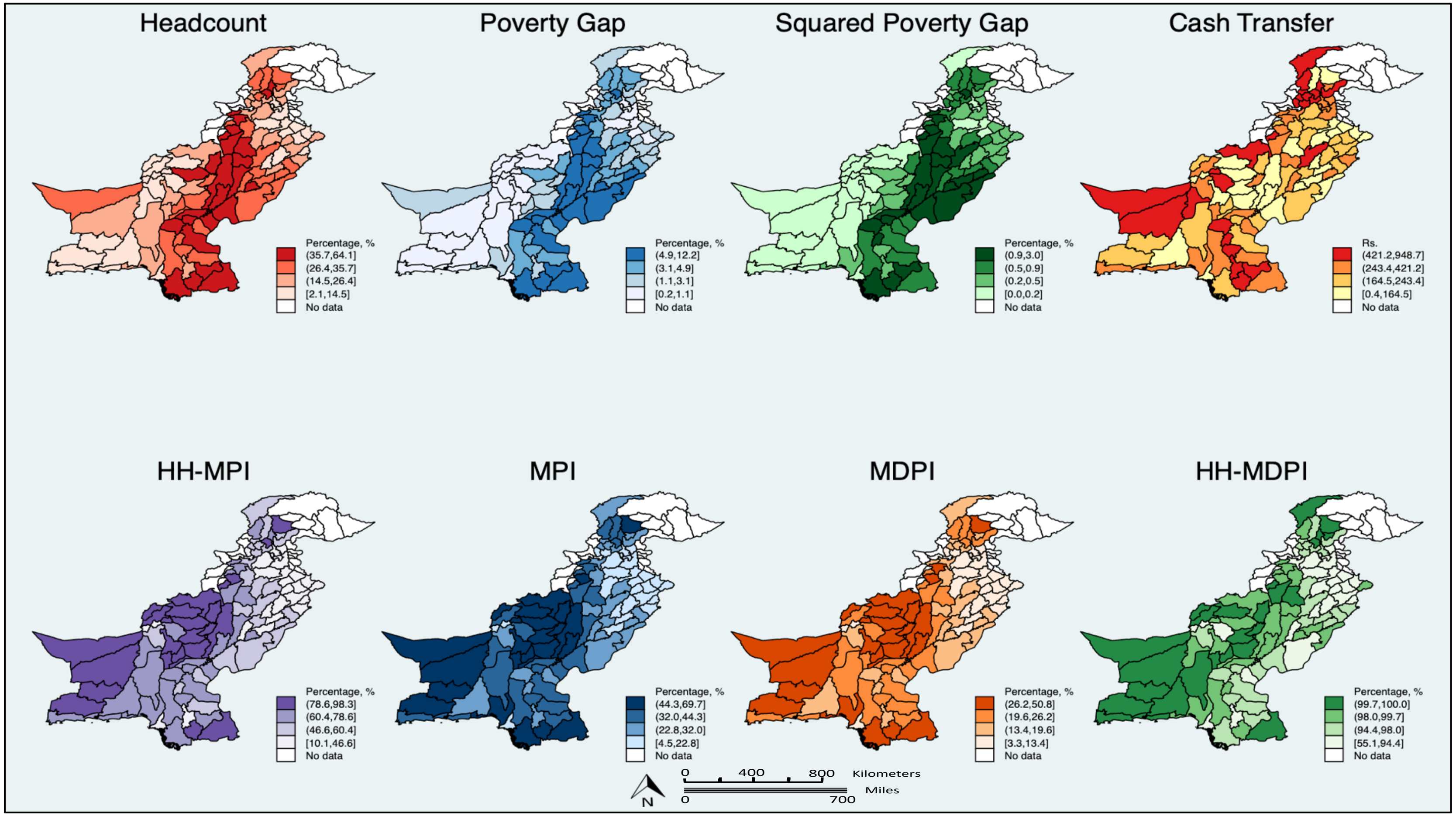
1. $Endowment = \Delta x\beta^{post}$
2. $Coefficient = \Delta\beta x^{post}$
3. $Interaction = (x^{\text{pre}} - x^{\text{post}})\, (\beta^{\text{pre}} - \beta^{\text{post}})$

Figure C1 Poverty and Cash Transfer Mapping– 2008



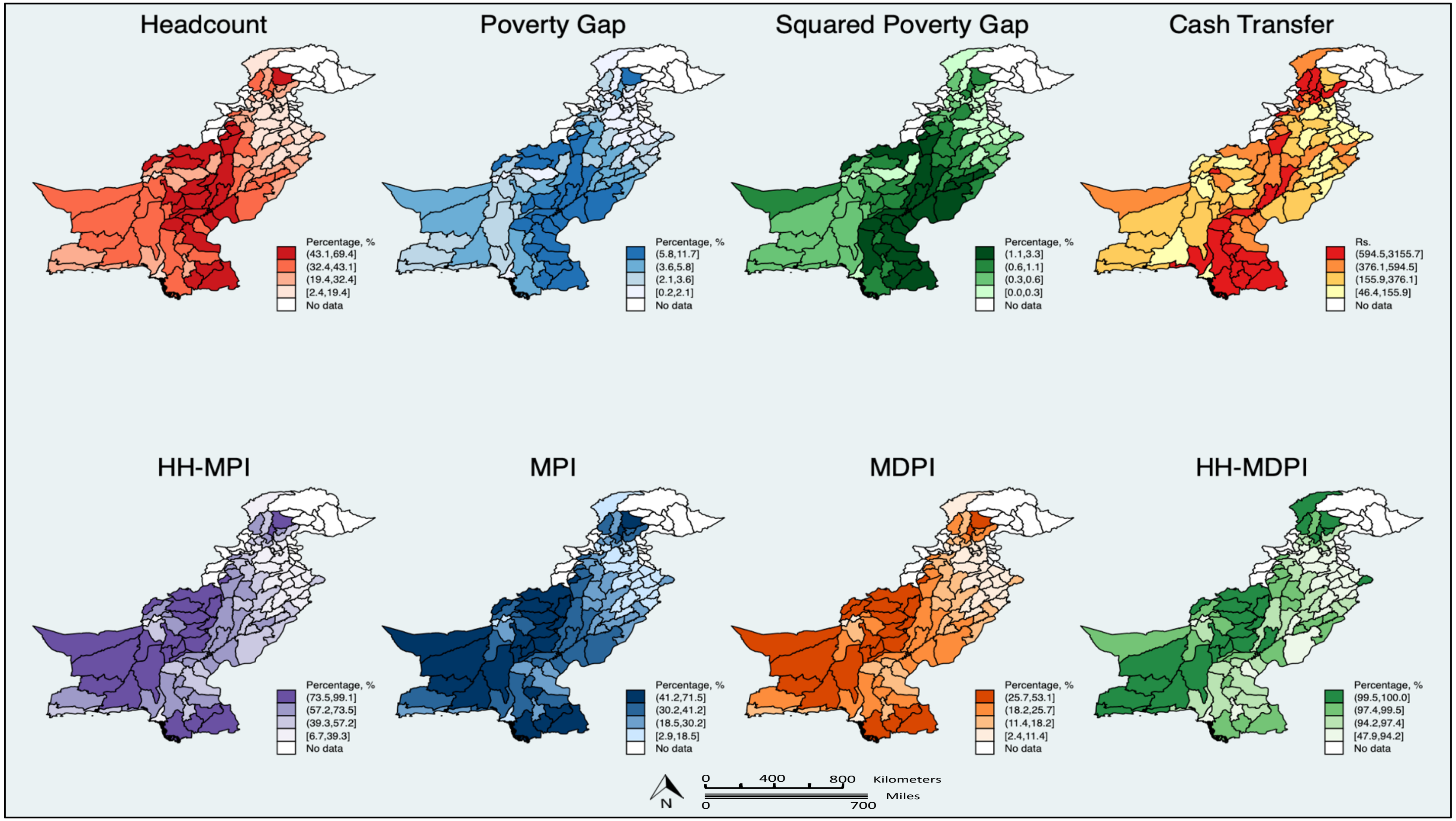
Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP)

Figure C2 Poverty and Cash Transfer Mapping– 2010



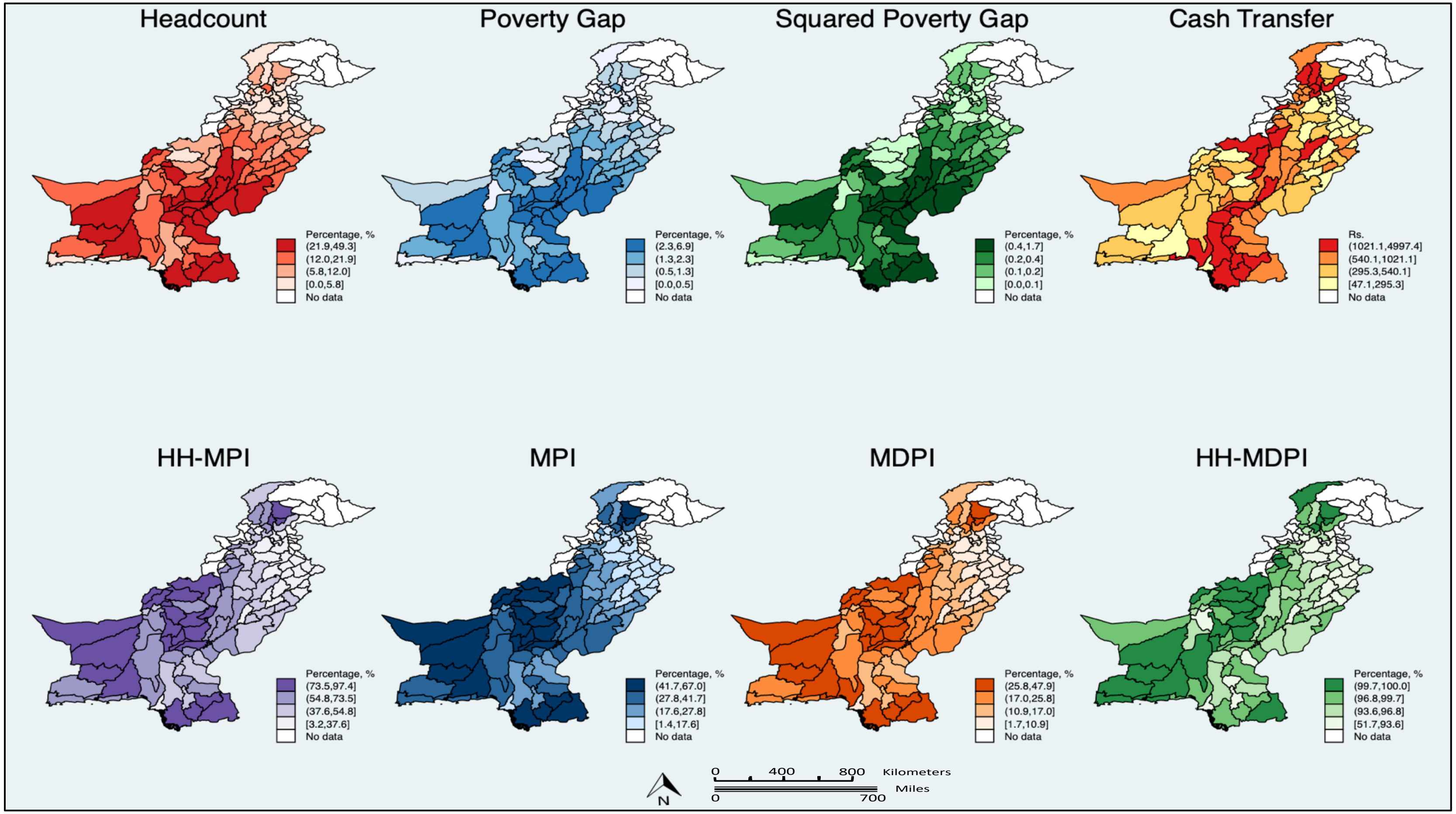
Notes: HH, Headcount Index; HH-MPI, Alkire & Foster (2011) Multidimensional Headcount Index; HH-MDPI, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP)

Figure C3 Poverty and Cash Transfer Mapping– 2012



Notes: HH, Headcount Index; HH-MPI, Alkire & Foster (2011) Multidimensional Headcount Index; HH-MDPI, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP

Figure C4 Poverty and Cash Transfer Mapping– 2014



Notes: HH, Headcount Index; HH-MPI, Alkire & Foster (2011) Multidimensional Headcount Index; HH-MDPI, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP)

Appendix D

Table D1: Blinder-Oaxaca Decomposition Headcount Index

Pre BISP	45.6*** (1.38)				
Post BISP	33.2*** (1.18)				
Difference	12.3*** (1.81)				
Endowment	5.9** (3.02)				
Coefficient	5.6*** (2.08)				
Interaction	0.7 (3.19)				
			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Young people < 15 years	210.5*** (47.75)	-23.1 (28.15)	-0.4 (0.52)	104.5*** (24.81)	4.3*** (1.39)
Adult people >35 & < 60 years	-102.9 (87.15)	-290.1*** (58.56)	3.1*** (0.82)	36.4* (20.45)	-2.02* (1.19)
Male headed Household	52.1 (32.91)	156.3*** (17.23)	-2.3*** (0.83)	-98.4*** (35.06)	1.5** (0.75)
High school in 30min return	3.4 (14.41)	-25.2** (13.75)	2.5* (1.44)	19.2 (13.41)	-2.8 (2.03)
Males	-3.6 (86.41)	-12.9 (49.97)	-0.04 (0.16)	4.7 (51.12)	0.03 (0.32)
Males who can read	2.11 (14.91)	-32.2*** (10.52)	1.48** (0.59)	22.6* (12.06)	-1.58* (0.92)
Hospital in 30 min return	-11.2 (14.48)	17.2 (13.25)	-1.6 (1.27)	-19.1 (13.16)	2.64 (1.89)
Own tractor	103.4** (42.68)	41.3 (30.25)	-0.1 (0.13)	2.23 (1.88)	-0.18 (0.22)
Own agriculture land	-2.8 (8.79)	12.5* (6.99)	1.07* (0.62)	-5.3 (3.87)	-1.3 (0.98)
Toilet facility	-1.2 (7.65)	-9.1* (4.90)	1.2* (0.69)	3.9 (4.56)	-1.06 (1.24)
Working population	-34.8** (17.97)	-106.4*** (10.14)	0.5 (0.77)	39.6*** (11.43)	-0.33 (0.52)
Own car	0.8 (32.86)	15.4 (20.30)	-0.15 (0.21)	-0.7 (1.94)	0.14 (0.38)
Concrete roof	0.7 (8.67)	5.5 (6.96)	0.4 (0.46)	-0.4 (0.88)	-0.31 (0.74)
More than 2 rooms	-6.8 (15.38)	-40.6*** (10.38)	-0.17 (0.36)	27.6* (15.17)	0.14 (0.31)
Child immunised	-6.3 (8.04)	8.1 (13.99)	-1.45 (2.51)	-13.7 (15.37)	2.58 (2.89)
Education till 10th	-36.2*** (12.68)	-16.4* (9.62)	0.32 (0.24)	-10.2 (8.19)	0.39 (0.36)
Access to electricity	-2.3 (8.18)	17.4** (7.71)	1.58** (0.76)	13.3 (9.83)	-1.4 (1.06)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D2: Blinder-Oaxaca Decomposition Poverty Gap Index

Pre BISP	8.21*** (0.35)				
Post BISP	5.36*** (0.27)				
Difference	2.84*** (0.44)				
Endowment	0.99*** (0.37)				
Coefficient	1.72*** (0.45)				
Interaction	0.13 (0.39)				
			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	-5.3 (24.45)	15.78 (12.11)	0.05 (0.05)	-10.8 (13.98)	-0.07 (0.10)
Young people < 15 years	60.9* (33.49)	28.06 (18.72)	0.51 (0.36)	14.7 (17.17)	0.6 (0.72)
Youth people <35 & > 15 years	15.8 (40.28)	43.2** (21.66)	-0.07 (0.11)	-8.63 (14.43)	0.04 (0.10)
Adult people >35 & < 60 years	3.34 (43.79)	11.2 (23.88)	0.12 (0.26)	2.82 (9.71)	-0.16 (0.54)
Male headed Household	13.7 (8.99)	30.48*** (4.40)	-0.44*** (0.17)	-15.8* (9.45)	0.24 (0.17)
Males who can read	-1.4 (3.74)	-6.23** (2.46)	0.28** (0.13)	3.17 (2.96)	-0.22 (0.21)
Education till 10th	-7.5** (3.63)	-4.3** (2.36)	0.09 (0.06)	-1.62 (2.23)	0.06 (0.09)
Working population	-9.2* (4.88)	-28.2*** (2.49)	0.13 (0.20)	10.54*** (3.04)	-0.09 (0.14)
Own car	5.6 (9.37)	5.8 (5.10)	-0.06 (0.05)	-0.01 (0.53)	0.002 (0.10)
Access to gas	1.5 (2.60)	-3.97*** (1.46)	0.29** (0.13)	1.23* (0.67)	-0.39* (0.24)
Toilet facility	-0.69 (2.12)	0.96 (1.22)	-0.13 (0.17)	-0.83 (1.23)	0.22 (0.33)
High school in 30min return	2.09 (3.93)	-10.3*** (3.41)	1.00*** (0.39)	8.32** (3.51)	-1.2** (0.57)
Own tractor	41.6*** (11.61)	17.2** (7.28)	-0.05 (0.05)	0.87* (0.49)	-0.07 (0.07)
More than 2 rooms	-6.4* (3.61)	-9.7*** (2.39)	-0.04 (0.08)	2.64 (3.54)	0.013 (0.03)
Hospital in 30 min return	-4.8 (3.85)	7.5** (3.32)	-0.69** (0.34)	-8.29** (3.41)	1.15** (0.52)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D3: Blinder-Oaxaca Decomposition Squared Poverty Gap Index

Pre BISP	2.07*** (0.11)				
Post BISP	1.27*** (0.08)				
Difference	0.79*** (0.13)				
Endowment	0.28*** (0.10)				
Coefficient	0.51*** (0.14)				
Interaction	0.016 (0.12)				
			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	0.14 (7.06)	8.62** (3.69)	0.03 (0.02)	-4.34 (4.08)	-0.03 (0.03)
Adult people >35 & <60 years	-20.6*** (5.17)	-13.73*** (2.95)	0.15*** (0.04)	-1.34 (1.16)	0.07 (0.06)
Male headed Household	6.35** (2.85)	9.47*** (1.29)	-0.14*** (0.05)	-2.93 (2.95)	0.04 (0.05)
Males who can read	-0.52 (1.19)	-1.43** (0.76)	0.14*** (0.05)	1.61* (0.94)	-0.11 (0.07)
Education till 10th	-2.88** (1.11)	0.28 (0.74)	0.03 (0.10)	-0.74 (0.68)	0.03 (0.03)
Own car	0.42 (2.84)	0.28 (1.13)	-0.002 (0.01)	0.007 (0.16)	-0.001 (0.03)
Own tractor	10.6*** (3.61)	4.34*** (2.16)	-0.012 (0.01)	0.22 (0.15)	-0.018 (0.02)
Working population	-1.99 (1.50)	-7.81*** (0.75)	0.04 (0.06)	3.22*** (0.93)	-0.03 (0.04)
High school in 30min return	1.19 (1.30)	-2.97*** (1.04)	0.29** (0.11)	2.8*** (1.12)	-0.41** (0.18)
Toilet facility	0.44 (0.69)	0.003 (0.45)	-0.0003 (0.06)	0.22 (0.41)	-0.06 (0.11)
Concrete walls	-1.24** (0.62)	1.14*** (0.47)	-0.09* (0.05)	-1.33*** (0.43)	0.19** (0.08)
Access to water in home	-0.09 (0.60)	-0.22 (0.30)	0.015 (0.02)	0.05 (0.26)	-0.008 (0.05)
Hospital in 30 min return	-1.89 (1.21)	1.74* (1.02)	-0.16 (0.10)	-2.43** (1.06)	0.33** (0.16)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D4: Blinder-Oaxaca Decomposition Multidimensional Poverty Index

Pre BISP	38.73*** (1.04)				
Post BISP	31.7*** (0.79)				
Difference	7.02*** (1.31)				
Endowment	5.52*** (1.30)				
Coefficient	0.81 (0.63)				
Interaction	0.69 (0.57)				
			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	60.8** (30.98)	15.3 (15.70)	0.048 (0.06)	23.3 (17.79)	0.14 (0.14)
Adult people >35 & <60 years	-99.4*** (22.70)	-79.6*** (12.47)	0.86*** (0.20)	-3.85 (5.04)	0.21 (0.28)
Males who can read	-24.5*** (4.93)	-34.4*** (3.23)	1.59*** (0.40)	6.58* (3.89)	-0.46 (0.29)
Education till 10th	-3.00 (4.57)	-7.49** (3.04)	0.15* (0.09)	2.31 (2.82)	-0.08 (0.11)
Male headed Household	28.8** (11.57)	9.93* (5.25)	-0.14 (0.09)	17.8 (11.99)	-0.27 (0.21)
Access to water in home	-2.99 (2.44)	-1.52 (1.17)	0.11 (0.09)	-0.57 (1.06)	0.10 (0.19)
Working population	-23.4*** (6.33)	-8.81*** (3.24)	0.04 (0.06)	-8.08** (3.93)	0.07 (0.11)
More than 2 rooms	-6.34 (5.18)	-3.93 (3.19)	-0.02 (0.04)	-1.97 (4.97)	-0.01 (0.03)
Hospital in 30 min return	-12.2** (4.99)	-14.23*** (4.18)	1.32*** (0.47)	1.36 (4.37)	-0.18 (0.61)
Concrete walls	-19.44*** (2.63)	-24.42*** (1.71)	1.97*** (0.66)	2.77 (1.75)	-0.4 (0.28)
Own tractor	7.92 (15.21)	1.14 (8.99)	-0.003 (0.03)	0.24 (0.63)	-0.019 (0.05)
Own agriculture land	0.97 (3.46)	-7.25*** (2.35)	-0.62*** (0.22)	2.83** (1.44)	0.7* (0.37)
High school in 30min return	0.49 (5.29)	0.65 (4.25)	-0.06 (0.42)	-0.11 (4.57)	0.01 (0.66)
Access to gas	-12.8*** (3.36)	-7.29*** (1.79)	0.53*** (0.18)	-1.25 (0.86)	0.4 (0.29)
Concrete roof	3.49 (3.02)	-3.73* (2.19)	-0.25* (0.15)	0.57** (0.30)	0.47* (0.26)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D5: Blinder-Oaxaca Decomposition Multidimensional Distribution-Sensitive Poverty Index

Pre BISP	24.78*** (0.74)				
Post BISP	20.06*** (0.52)				
Difference	4.72*** (0.90)				
Endowment	2.58*** (0.82)				
Coefficient	1.13 (0.86)				
Interaction	1.00 (0.81)				
			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	42.57 (28.19)	-8.1 (12.95)	-0.02 (0.04)	25.94 (16.23)	0.16 (0.14)
Concrete roof	1.22 (2.75)	-4.63*** (1.81)	-0.31** (0.13)	0.46* (0.26)	0.39* (0.23)
Adult people >35 & <60 years	-80.27*** (19.33)	-48.7*** (10.21)	0.53*** (0.14)	-6.15 (4.25)	0.34 (0.24)
Male headed Household	26.6*** (10.51)	12.9*** (4.34)	-0.19** (0.09)	12.93 (10.73)	-0.19 (0.18)
Working population	-11.5** (5.54)	-2.96 (2.53)	0.014 (0.02)	-4.76 (3.37)	0.04 (0.07)
Education till 5th	-5.7 (9.94)	-4.84*** (1.52)	-0.26*** (0.08)	-0.74 (8.47)	-0.05 (0.54)
Education till 10th	-1.94 (5.31)	-8.86*** (2.54)	0.17* (0.09)	3.56 (3.03)	-0.14 (0.13)
Access to gas	-10.26*** (3.25)	-4.95*** (1.52)	0.36** (0.14)	-1.2 (0.81)	0.39 (0.28)
Access to water in home	-3.61 (2.28)	-2.95*** (0.96)	0.21** (0.08)	-0.26 (0.96)	0.05 (0.17)
High school in 30min return	-2.7 (4.74)	-2.42 (3.51)	0.24 (0.35)	-0.21 (3.96)	0.03 (0.58)
Concrete walls	-12.93*** (2.43)	-17.95*** (1.28)	1.44*** (0.48)	2.8* (1.54)	-0.40 (0.26)
Own tractor	2.34 (13.91)	2.22 (7.80)	-0.006 (0.02)	0.004 (0.57)	-0.0003 (0.04)
Hospital in 30 min return	-12.88*** (4.58)	-11.58*** (3.44)	1.08*** (0.38)	-0.87 (3.84)	0.12 (0.53)
Own agriculture land	-4.23 (2.82)	-9.14*** (1.82)	-0.78*** (0.20)	1.69 (1.16)	0.42 (0.29)
Own car	4.35 (11.28)	-10.35** (4.93)	0.100 (0.06)	0.74 (0.62)	-0.14 (0.13)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D6: Blinder-Oaxaca Decomposition MPI Headcount Index

Pre BISP	68.29*** (1.45)				
Post BISP	58.08*** (1.19)				
Difference	10.21*** (1.88)				
Endowment	8.04*** (1.89)				
Coefficient	1.06 (0.77)				
Interaction	1.10 (0.69)				
			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	138.18*** (28.51)	69.69*** (22.46)	0.22 (0.16)	35.07* (18.59)	0.22 (0.18)
Young people <15 years	115.09*** (19.05)	64.8*** (14.44)	1.19*** (0.37)	22.5** (10.70)	0.92* (0.48)
Adult people >35 & <60 years	-58.89* (34.85)	-69.91** (28.22)	0.76** (0.33)	2.14 (8.73)	-0.12 (0.48)
Education till 10th	-4.48 (5.28)	-14.61*** (5.02)	0.28* (0.16)	5.21 (3.75)	-0.2 (0.17)
Working population	-11.62* (7.00)	-7.83 (5.23)	0.04 (0.06)	-2.1 (4.84)	0.02 (0.05)
Own tractor	16.46 (18.11)	34.9** (15.59)	-0.100 (0.09)	-0.66 (0.86)	0.05 (0.08)
Own agriculture land	-1.30 (3.89)	-10.62*** (3.90)	-0.91** (0.36)	3.2* (1.89)	0.79 (0.49)
Own car	-8.98 (14.38)	-20.26** (10.52)	0.19 (0.13)	0.57 (0.89)	-0.11 (0.18)
More than 2 rooms	-6.17 (6.12)	-19.45*** (5.31)	-0.08 (0.17)	10.8 (6.62)	0.05 (0.12)
Concrete roof	8.11** (3.55)	-0.44 (3.53)	-0.03 (0.23)	0.67* (0.40)	0.56 (0.35)
Hospital in 30 min return	2.59 (5.77)	-29.01*** (6.92)	2.69*** (0.84)	21.2*** (6.05)	-2.94*** (1.02)
High school in 30min return	-8.91 (5.83)	13.5* (7.12)	-1.33* (0.75)	-15.1** (6.20)	2.2** (1.00)
Access to water in home	-2.94 (2.85)	-3.6* (1.89)	0.26* (0.15)	0.28 (1.33)	-0.05 (0.24)
Access to gas	-30.58*** (4.13)	-18.55*** (3.07)	1.35*** (0.39)	-2.72** (1.17)	0.87** (0.43)
Concrete walls	-28.6*** (3.10)	-43.26*** (2.67)	3.49*** (1.16)	8.18*** (2.29)	-1.18** (0.51)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D7: Blinder-Oaxaca Decomposition MDPI Headcount Index

Pre BISP	97.05*** (0.44)				
Post BISP	95.01*** (0.41)				
Difference	2.03*** (0.60)				
Endowment	1.55*** (0.43)				
Coefficient	0.42 (0.55)				
Interaction	0.05 (0.36)				
			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	-1.03 (25.66)	-17.65 (17.78)	-0.05 (0.06)	8.51 (15.99)	0.05 (0.10)
Young people <15 years	97.12*** (12.93)	85.46*** (9.09)	1.57*** (0.39)	5.21 (7.07)	0.21 (0.29)
Adult people >35 & <60 years	16.9 (26.71)	-24.55 (20.50)	0.26 (0.22)	8.08 (6.55)	-0.45 (0.37)
Male headed Household	-10.68 (11.03)	7.25 (6.63)	-0.10 (0.10)	-16.93 (12.15)	0.26 (0.21)
Working population	7.36 (5.44)	0.23 (3.50)	-0.001 (0.02)	3.94 (3.58)	-0.03 (0.06)
Own tractor	36.63*** (13.77)	40.88*** (10.78)	-0.12 (0.11)	-0.15 (0.63)	0.012 (0.05)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Appendix E

Table E1: Fixed-Effect Panel Regression: Headcount Index

Variables	Model 1	Model 2
Phase		40.82* (24.43)
Log Cash Transfer × Phase I		-2.16* (1.28)
Log Cash Transfers	-10.8*** (1.38)	-11.25*** (1.59)
Male headed Household	72.03*** (19.4)	64.16*** (19.86)
Males who can read	-36.2** (16.7)	-43.22*** (16.21)
Working population	-106.3*** (13.5)	-102.40*** (13.81)
Own agriculture land	-33.14*** (12.8)	-25.63** (12.89)
Access to gas	-61.4*** (12.1)	-66.71*** (12.00)
Access to electricity	-21.5* (12.7)	
High school in 30min return	-7.02 (6.8)	
R sq within	0.6327	0.6307
R sq between	0.3002	0.2805
R sq overall	0.3619	0.3535
Sigma_u	21.8	21.65
Sigma_e	13.8	13.81
Corr(u_i, Xb)	-0.7395	-0.7325
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E2: Fixed-Effect Panel Regression Poverty Gap Index

	Model 1	Model 2
Phase		18.70*** (6.15)
Log Cash Transfer × Phase I		-0.98*** (0.32)
Log Cash Transfers	-1.93*** (0.34)	-1.79*** (0.39)
Males	5.67 (14.5)	9.56 (14.40)
Male headed Household	8.8* (4.89)	6.48 (4.99)
Males who can read	-5.46 (4.15)	-4.83 (4.11)
Working population	-38.24*** (3.36)	-36.29*** (3.38)
Access to gas	-8.19*** (3.17)	-12.89*** (2.98)
Access to electricity	-11.7*** (2.98)	-8.42*** (3.19)
High school in 30min return	-10.51*** (3.14)	-2.70 (1.70)
R sq within	0.6375	0.6490
R sq between	0.1198	0.1242
R sq overall	0.2778	0.2799
Sigma_u	5.48	5.60
Sigma_e	3.40	3.36
Corr(u_i, Xb)	-0.7466	-0.7547
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E3: Fixed-Effect Panel Regression Squared Poverty Gap Index

	Model 1	Model 2
Phase		5.69*** (0.12)
Log Cash Transfer × Phase I		-0.30*** (0.09)
Log Cash Transfers	-0.49*** (0.101)	-0.44*** (0.12)
Males	2.56 (4.3)	3.73 (4.28)
Male headed Household	1.43 (1.45)	0.71 (1.48)
Males who can read	-1.13 (1.23)	-0.93 (1.22)
Working population	12.7*** (0.99)	-12.08*** (1.00)
Access to gas	-2.95*** (0.89)	-3.30*** (0.88)
Access to electricity	-3.61*** (0.93)	-2.97*** (0.95)
High school in 30min return	-1.09** (0.5)	-0.93* (0.50)
R sq within	0.6400	0.6519
R sq between	0.0339	0.0368
R sq overall	0.2321	0.2356
Sigma_u	1.67	1.69
Sigma_e	1.01	1.00
Corr(u_i, Xb)	-0.7443	-0.7496
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E4: Fixed-Effect Panel Regression Multidimensional Poverty Index

	Model 1	Model 2
Phase		-24.62*** (6.57)
Log Cash Transfer × Phase I		1.34*** (0.34)
Log Cash Transfers	-0.97*** (0.38)	-1.58*** (0.42)
Male	14.09 (14.7)	21.03 (15.00)
Adult people >35 & <60 years	-86.5*** (16.4)	-68.37*** (16.81)
Males who can read	-32.8*** (4.3)	-37.28*** (4.32)
Education till 10th	-11.12*** (2.98)	-15.08*** (3.04)
Access to water in home	-2.37** (1.26)	-
Working population	-9.62*** (3.51)	-12.73*** (3.67)
More than 2 rooms	-4.32 (4.45)	-10.42** (4.54)
Hospital in 30 min return	-9.22*** (1.75)	-
Own tractor	-9.06 (10.73)	-
Own agriculture land	-11.35*** (3.44)	-12.85*** (3.40)
Access to gas	-12.96*** (3.21)	-14.24*** (3.13)
Concrete roof	-3.46 (2.33)	-2.88 (2.39)
R sq within	0.5756	0.5557
R sq between	0.8084	0.6738
R sq overall	0.7742	0.6494
Sigma_u	8.21	9.72
Sigma_e	3.48	3.55
Corr(u_i, Xb)	0.5475	0.4185
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E5: Random-Effect Panel Regression Multidimension Distribution-sensitive Poverty Index

	Model 1	Model 2
Phase		-7.95 (6.10)
Log Cash Transfer × Phase I		0.35*** (0.32)
Log Cash Transfers	-0.82*** (0.26)	-1.21*** (0.27)
Concrete roof	-5.42*** (1.89)	-4.19** (1.95)
Adult people >35 & <60 years	-36.77** (15.76)	-36.13** (15.76)
Education till 10th	-7.47*** (2.57)	-8.32*** (2.60)
Males	31.16*** (11.64)	35.13*** (11.62)
Access to gas	-10.92*** (1.97)	-10.70*** (1.95)
High school in 30min return	-2.95 (3.51)	-2.48 (3.50)
Own car	-7.93 (5.92)	-8.66 (5.88)
Young people	40.83*** (7.32)	40.12*** (7.30)
Own agriculture land	-8.84*** (2.26)	-8.75*** (2.25)
Access to water in home	-0.59 (1.07)	-1.11 (1.19)
Hospital in 30 min return	-12.59*** (10.82)	13.58*** (3.38)
R sq within	0.4161	0.4167
R sq between	0.8192	0.8252
R sq overall	0.7642	0.7715
Sigma_u	3.13	3.03
Sigma_e	2.96	2.95
Corr(u_i, Xb)	RE	RE

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E6: Fixed-Effect Panel Regression MPI Headcount Index

	Model 1	Model 2
Phase		-31.47*** (8.52)
Log Cash Transfer × Phase I		1.79*** (0.45)
Log Cash Transfers	-0.96* (0.55)	-1.81** (0.55)
Male	49.61*** (19.66)	43.28** (19.60)
Youth people >15 & <35 years	-33.24*** (12.85)	-39.96*** (12.55)
Adult people >35 & <60 years	-80.57*** (22.0)	-81.72*** (21.99)
Male who can read	-31.07*** (5.9)	-36.77*** (5.69)
More than 2 rooms	-7.97 (5.96)	-12.27** (5.95)
Own car	-3.58 (12.2)	-
Education till 10th	-14.4*** (4.1)	-15.59*** (4.06)
Working population	-11.54*** (4.69)	-10.13** (4.66)
Access to water in home	-1.46 (1.76)	-
Own agriculture land	-12.47*** (4.69)	-15.09*** (4.60)
Access to toilet in home	-7.38*** (2.51)	-
Own tractor	-27.2* (15.7)	-27.48* (14.33)
Access to gas	-13.07*** (4.46)	-11.67** (4.39)
Hospital in 30 min return	-9.65*** (2.44)	-10.47*** (2.32)
Concrete walls	-17.47*** (6.1)	-
R sq within	0.5878	0.5889
R sq between	0.9124	0.7887
R sq overall	0.8853	0.7426
Sigma_u	9.16	14.67
Sigma_e	4.64	4.62
Corr(u_i, Xb)	0.6420	0.6287
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E7: Random-Effect Panel Regression MDPI Headcount Index

	Model 1	Model 2
Phase		-4.59 (3.44)
Log Cash Transfer × Phase I		0.26 (0.18)
Log Cash Transfers	-0.28* (0.16)	-0.19 (0.19)
Male	8.32 (7.68)	9.39 (7.64)
Education till 10th	-2.42 (1.60)	-4.59*** (1.57)
Adult people >35 & <60 years	-41.57*** (8.12)	-34.47*** (8.21)
Hospital in 30 min return	-3.39* (2.06)	-
High school in 30min return	-1.58 (2.10)	-
Own car	-27.61*** (3.99)	-20.99*** (3.96)
R sq within	0.1490	0.1790
R sq between	0.7198	0.6741
R sq overall	0.6323	0.5748
Sigma_u	3.93	3.83
Sigma_e	1.67	1.56
Corr(u_i, Xb)	RE	RE

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

CHAPTER 8

Conclusion

An awareness of how conclusions drawn from poverty analyses change following introduction of multidimensional poverty measures is crucial for policy makers. Currently, many countries are transitioning into the use of multidimensional poverty measures and so the nature of new evidence differs from what was learned in the past from money-metric poverty measures. This thesis contributes to understanding on this topic by providing evidence from Pakistan that the regional poverty profiles, the temporal poverty trends and the progress towards eradicating poverty are no longer the same with multidimensional poverty measures compared to what facts are established previously with money-metric poverty measures. The findings are timely for Pakistan, as around 40 percent of the population is at risk of moving into poverty (Planning Commission Pakistan, 2018) and the shocks such as Covid-19 have created more intense interest in the impacts on poverty.

My district level analysis shows clusters of the poorest areas across the country. However the multidimensional and money-metric poverty measures show different spatial patterns of those clusters. The districts which fall into the top-tier of money-metric poverty are not those which fall into the top-tier of multidimensional poverty. The money-metric poverty measures show the poorest regions to be in the south of Punjab, the south of Sindh and some in Balochistan However, multidimensional poverty measures show the poorest regions to be in Balochistan and Sindh.

There are discordant poverty trends when poverty is analysed using multidimensional instead of conventional money-metric poverty measures. Around two-thirds of districts show opposite trends for at least two of the five spells between surveys (for the six surveys fielded from 2004 to 2014) when poverty trends are calculated using money-metric and multidimensional poverty measures. Moreover, the multidimensional poverty measures showed much less fluctuation than did the conventional money-metric poverty measures, especially in 2008 when Pakistan was faced with the global financial crisis and the highest inflation in many years. Money-metric poverty estimates seem to be affected by the transitory economic shocks, but multidimensional poverty estimates are not and so one would not want to put full reliance on multidimensional measures in settings where there is a considerable degree of economic volatility.

When my analysis considered distribution-sensitive poverty measures, that is convexity in deprivation, the multidimensional and money-metric measures also revealed different poverty trends. The provincial-level analysis of the most developed province, Punjab, showed similar poverty trends for the distribution-insensitive money-metric (PG) and multidimensional (MPI) poverty measures. However, different poverty trends are apparent for analysis done using the distribution-sensitive class of poverty measures – SPG from money-metric measures and MDPI from multidimensional measures. Even different spatial poverty profiles are evident for these different poverty measures. In Punjab, districts with high Squared Poverty Gap Index values do not have the highest headcount rate. This implies that over the ten years (2004-2014), although poverty headcount numbers are reducing in some districts of Punjab the severity of poverty is not.

The evidence of convergence in poverty is also sensitive to the choice of poverty measure. The convergence in poverty is evident at the district level for money-metric poverty measures but not for multidimensional poverty measures. The districts which had high initial money-metric poverty are catching up with their counterparts. Whereas, the districts with initially high incidence of multidimensional poverty are not catching up to their counterparts. Also, cross-district spillovers from spatial regression models matter only for money-metric poverty and not for multidimensional poverty. One reason why spatial spillovers are not significant in the case of multidimensional poverty measures is these indices measure access to services and facilities which are reliant on government's development initiatives. And in Pakistan there is regional polarisation in the development priorities of the government (Sandilah & Yasin, 2011).

The estimated effects of growth in big cities versus growth in secondary towns in eradicating rural poverty differ for money-metric and multidimensional poverty measures. In Pakistan, the big cities are growing faster than the secondary towns (based on the analysis of night-time lights data). However, the growth in big cities is not reducing multidimensional poverty in rural areas. Instead, the form of urban growth resulting from government development initiatives concentrated on big cities may be directing the resources away from secondary towns and rural areas, hence increasing the rural multidimensional poverty. The development initiatives are focused on the big cities, as most urbanisation is seen in a small number of very large cities in Pakistan (Blank et al., 2014). As opposed to multidimensional poverty measures, for the headcount index of money-metric poverty, growth in big cities is associated with lower rural poverty, although that growth does not seem to reach the poorest of the poor (based on results for the squared poverty gap index). The growth of towns on their extensive margin (expansion of lit area rather than greater brightness) is associated with lower money-metric rural poverty. Once again, key patterns for analysing the outcomes of economic development on poverty in Pakistan are sensitive to the type of poverty measures used.

The fourth case presented in my thesis shows that evaluation of social safety net programmes is also sensitive to choice of poverty measure. The Government of Pakistan's largest social safety net programme, Benazir Income Support Programme (BISP) which began in 2008, is significant in reducing money-metric poverty and multidimensional poverty. However, the size of the impact is smaller for multidimensional poverty. Furthermore, if convexity in deprivation (distribution-sensitivity) is considered, the effect of BISP becomes marginal. Also, BISP has been through two targeting methods, Community Based Targeting (CBT) and Proxy Means Testing (PMT), and it turns out that in terms of reducing money-metric poverty CBT seems more effective whereas in reducing multidimensional poverty PMT is more effective.

Before summing up the conclusions drawn in this thesis, there a few limitations of the analysis conducted. As discussed in chapter four, HIES is not representative at the district level hence I relied on Small Area Estimation to estimate money-metric poverty measures. Although all the pre-requisites for SAE are satisfied, SAE has its own limitation of how accurately it can impute. Nonetheless, the money-metric poverty trends from SAE in this thesis are robust. Also, this research relied on poverty lines estimated officially in Pakistan and is adjusted for inflation for the years it was not available. The night-time lights data used in chapter six is sourced from (Defense Meteorological Satellite Program) DMSP whereas the better quality night-time lights data adjusted for blurring and top coding from Visible Infrared Imaging Radiometer Suite (VIIRS) are not available prior to 2011.

To sum up, a consistent finding in this thesis is that patterns that hold for money-metric poverty (that are evident in the existing literature) may not hold for multidimensional poverty. Thus, after the introduction of multidimensional poverty measures, poverty patterns are no longer seen in the usual manner that was established from prior studies using money-metric poverty. Consequently, at least in the transition period while multidimensional poverty measures are supplanting or supplementing more traditional money-metric measures, policy makers need to be more cautious in the conclusions they draw from poverty analyses. Beyond Pakistan, as there is an increased number of countries switching to the use of multidimensional measures, information around which patterns change, due to a shift in what is measured, instead of noticing what changes on the ground, will be imperative for strengthening our understanding of poverty and of development in order to make progress towards meeting the Sustainable Development Goals. This contribution to the knowledge base will also be imperative in devising intervention strategies during uncertain situations like COVID-19.

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Appendix I

No	Study	Title	Scope	Journal
1	Joekes et al. (2000)	Poverty reduction without human development in Pakistan: money doesn't buy you everything	National	Development Policy Review
2	Qureshi and Arif (2001)	Profile of poverty in Pakistan 1998-99	Rural and Urban	Pakistan Institute of Development Economics
3	Bhatti et al. (1999)	A sectoral analysis of poverty in Pakistan	National with sectoral decomposition	The Pakistan Development Review
4	Anwar and Qureshi (2002)	Trends in absolute poverty in Pakistan: 1990-91 and 2001	Provincial	The Pakistan Development Review
5	Ali and Tahir (1999)	Dynamics of growth, poverty, and Inequality in Pakistan	Rural and Urban	The Pakistan Development Review
6	Jafri et al. (1995)	Income inequality and poverty in Pakistan	National	Pakistan Economic and Social Review
7	Allaudin (1975)	Mass poverty in Pakistan	Rural and Urban	The Pakistan Development Review
8	Naseem (1976)	Mass poverty in Pakistan: some preliminary findings	Rural and Urban	The Pakistan Development Review
9	Ali (1995)	Poverty assessment: Pakistan's case	National	The Pakistan Development Review
10	Mujahid (1978)	A note on measurement of poverty and income inequalities in Pakistan: Some observations on methodology	National	The Pakistan Development Review
11	De Kruijk et al. (1985)	Changes in poverty and income inequality in Pakistan during the 1970s	Rural and Urban	Pakistan Development Review
12	Ahmad et al. (1989)	Poverty, inequality, and growth in Pakistan	Rural and Urban	The Pakistan Development Review

No	Study	Title	Scope	Journal
13	Zaidi et al. (1993)	Research on poverty statistics in Pakistan some sensitivity analysis	Provincial	The Pakistan Development Review
14	Havinga et al. (1989)	Poverty in Pakistan (1984-85)	Provincial, Rural and Urban	The Pakistan Development Review
15	Naseem (1977)	Rural poverty and landlessness in Pakistan	National	In ILO Report on Poverty and Landlessness in Asia. Geneva: International Labour Office
16	Irfan and Amjad (1994)	Poverty in rural Pakistan	Provincial	MPRA Working Paper
17	Malik and Choudhary (1992)	Rural poverty in Pakistan	Provincial	The Pakistan Development Review
18	Malik et al. (1994)	Role of Infaq in poverty alleviation in Pakistan	Provincial	The Pakistan Development Review
19	Amjad and Kemal (1997)	Macroeconomic policies and their impact on poverty alleviation in Pakistan	Rural and Urban	The Pakistan Development Review
20	Anwar & Iqbal (1996)	Structural adjustment and poverty; the case of Pakistan	Provincial	The Pakistan Development Review
21	Zaidi (1992)	Relative poverty in Pakistan an estimation from the household income and expenditure survey (1984-85)	Provincial	The Pakistan Development Review
22	Arif et al. (2000)	Rural non-agriculture employment and Poverty in Pakistan	National	The Pakistan Development Review
23	Malik (1988)	Some new evidence on the incidence of poverty in Pakistan	National	The Pakistan Development Review
24	Jamal (2007)	Income poverty at district-level: an Application of small area estimation Technique	District	Social Policy and Development Centre

No	Study	Title	Scope	Journal
25	Arif and Bilquees (2007)	Chronic and Transitory Poverty in Pakistan: Evidence from a Longitudinal Household Survey	Provincial	The Pakistan Development Review
26	Arif and Farooq (2014)	Rural Poverty Dynamics in Pakistan: Evidence from Three Waves of the Panel Survey	16 Districts	The Pakistan Development Review
27	Kurosaki (2006)	The Measurement of Transient Poverty: Theory and Application to Pakistan	District (Peshawar)	The Journal of Economic Inequality
28	Lohana (2009)	Poverty Dynamics in Rural Sindh, Pakistan	Provincial (Sindh)	Chronic Poverty Research Centre Working Paper
29	Khurram and Hassan (2019)	Exploring the Incidence and Correlates of Rural Poverty in Pakistan	District (Bhakkar)	Pakistan Economic and Social Review
30	Farooq and Ahmad (2020)	Economic Growth and Rural Poverty in Pakistan: A Panel Dataset Analysis	Provincial	The European Journal of Development Research
31	Khan et al. (2020)	An empirical analysis of monetary and multidimensional poverty: evidence from a household survey in Pakistan	District (Mandi Bahuddin)	Asia Pacific Journal of Social Work and Development
32	Azeem et al. (2018)	Vulnerability to Multi-Dimensional Poverty: An Empirical Comparison of Alternative Measurement Approaches	Provincial (Punjab)	The Journal of Development Studies
		MULTIDIMENSIONAL		
33	UNDP (2016)	Multidimensional poverty in Pakistan	District	Planning Commission of Pakistan Report
34	Cheema et al. (2008)	The geography of poverty: evidence from the Punjab	District (Punjab)	The Lahore Journal of Economics
35	Naveed and Ali (2012)	Clustered deprivation: District profile of poverty in Pakistan	District	Sustainable Development Policy Institute (SDPI) report

No	Study	Title	Scope	Journal
36	Salahuddin and Zaman (2012)	Multidimensional poverty measurement in Pakistan: Time series trends and breakdown	Provincial	The Pakistan Development Review
37	Awan et al. (2015)	Multidimensional measurement of Poverty in Pakistan	Provincial	Economic Working Papers
38	Awan et al. (2013)	An investigation of multidimensional energy Poverty in Pakistan	National	The Pakistan Development Review
39	Jamal (2011)	Assessing poverty with non-income deprivation Indicators: Pakistan (2008-09)	District	The Pakistan Development Review
40	Jamal (2012)	An exploratory analysis of inter-temporal Multidimensional poverty	District	SPDC Research Report
41	Khan et al. (2014)	Investigating multidimensional poverty Across the regions in the Sindh province of Pakistan	District (Sindh)	Social indicators research
42	Said et al. (2011)	Macro level determinants of poverty: Investigation through poverty mapping of districts of Pakistan	District	The Pakistan Development Review
43	Sial et al. (2015)	Measuring multidimensional poverty and Inequality in Pakistan	National	The Pakistan Development Review
44	Saboor et al. (2015)	Multidimensional deprivations in Pakistan: regional variations and temporal shifts	26 Administrative Regions	The Quarterly Review of Economics and Finance
45	Awan et al. (2015)	Multidimensional measurement of poverty in Pakistan: provincial analysis	Provincial	Economic Working Papers
46	Begum (2015)	The livelihood and poverty mapping analysis at regional level in Pakistan	District	Thesis; Wageningen University and Research Centre
47	Khan et al. (2016)	Urbanization of multidimensional poverty: empirical Evidences from Pakistan	Administrative divisions	Quality & Quantity

No	Study	Title	Scope	Journal
48	Saleem et al. (2019)	Re-examining multidimensional poverty in Pakistan: A new assessment of regional variations	Rural and Urban	Global Business Review
49	Idrees (2017)	Poverty in Pakistan: A Region-Specific Analysis	Rural and Urban	The Lahore Journal of Economics,
50	Azeem et al. (2018)	Vulnerability to Multi-Dimensional Poverty: An Empirical Comparison of Alternative Measurement Approaches.	Provincial (Punjab)	The Journal of Development Studies
51	Khan and Akram (2018)	Sensitivity of multidimensional poverty index in Pakistan	Provincial	The Pakistan Journal of Social Issues
52	Khan et al. (2020)	An empirical analysis of monetary and multidimensional poverty: evidence from a household survey in Pakistan.	District (Mandi Bahuddin)	Asia Pacific Journal of Social Work and Development
53	Idrees and Baig (2017)	An Empirical Analysis of Multidimensional Poverty in Pakistan	National	Journal of Social Sciences
54	Padda and Hameed (2018)	Estimating multidimensional poverty levels in rural Pakistan: A contribution to sustainable development policies.	Districts (19 Rural areas)	Journal of Cleaner Production
55	Saleem and Khan (2017)	Multidimensional poverty in Pakistan: a policy perspective.	Provincial	In Proceedings of the International Conference on Poverty and Sustainable Development

LITERATURE SUMMARY TABLE

POVERTY MEASURES	PROPERTIES	PUBLICATIONS
CONVENTIONAL	Distribution insensitive	1,2,4,5,6,7,8,9,10,11,12,13,14,15,17,16,17,18,19,20, 21,22,23,24,25,26,27,28,29,30,31,32
	Distribution Sensitive	1,2,3,4,6,11,12,16,17,18,19,20,21,22,24,27,28,29,31
NON CONVENTIONAL	Distribution Insensitive	33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55
	Distribution sensitive	Not Available

Appendix II

Co-Authorship Form

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Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 5

Najam, Z. & Gibson, J. (2021). Does within-country poverty convergence depend on spatial spillovers and the type of poverty measure? Evidence from Pakistan. *Working Paper* No. 21/07, Department of Economics, University of Waikato.

Nature of contribution by PhD candidate	Conceptualisation of study, data cleaning, estimation, analysis, and write-up
Extent of contribution by PhD candidate (%)	80

CO-AUTHORS

Name	Nature of Contribution
John Gibson	Critical feedback during conceptualisation of study, guidance, support in making the narrative effective for the audience and thoroughly reviewed the article.

Certification by Co-Authors

The undersigned hereby certify that:
the above statement correctly reflects the nature and extent of the PhD candidate’s contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
John Gibson	John Gibson	30/8/21

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Co-Authorship Form

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Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 7

Najam, Z. & Olivia S. (2021). Does the impact of cash transfers differ across poverty measures? Evidence from Pakistan. *Working Paper* No. 21/09, Department of Economics, University of Waikato.

Nature of contribution by PhD candidate	Conceptualisation of study, data cleaning, estimation, analysis, and write-up
Extent of contribution by PhD candidate (%)	80

CO-AUTHORS

Name	**Nature of Contribution**
Susan Olivia	Critical feedback, guidance in structure of study, support in putting across the narrative effectively, and thoroughly reviewed the article.

Certification by Co-Authors

The undersigned hereby certify that:
the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	**Signature**	Date
Susan Olivia	Susan Olivia	30/8/2021