Essays on Poverty, Inequality and Education in India and Pakistan

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This dissertation is dedicated to my Family

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Contents

List of Tables

Chapter 1

Introduction to the Essays

Over the last century, the world has accomplished a tremendous achievement in reaching higher economic growth rates. A cross-country comparison shows that most countries are better off than previously. The world's GDP per capita improved to 14,574 USD in 2016 from 3,300 USD in 1950, which is almost 4.4 times as rich as in 1950 (Inklaar et al. 2018). However, some regions report higher gains in terms of output and productivity than others. During this phase of development, the first stylized fact of economic development emerges, that is initially poor and backward countries grow more quickly than their counterparts. This is what we call the advantages of backwardness.

The process of economic growth in less developed countries has rebounded since 1990, following slow progress during the 1980s (Bluedorn et al. 2013). A key question needs to be addressed here whether this stronger takeoff of growth has distributed its fruits to the poor people or not. The higher pace of economic growth has translated into a faster rate of poverty reduction in the developing world. This fact provides the basis for the second stylized fact, the advantages of growth. This has found considerable support in the literature.[1]

The less developed countries that enjoyed a higher economic growth rate have made marvelous improvements in poverty reduction. The incidence of poverty across the world reduced to 10.7 percent in 2016 when compared to 35 percent in 1990 (World Bank 2016). Based on this significant reduction in poverty and the aforementioned two stylized facts of economic development, Ravallion (2012) proposed

[1] Ravallion and Chen (1999); Ravallion et al. (1999); World Bank (2000); Dollar and Kraay (2002); Bourguignon (2003); Ravallion (2012); Klasen and Misselhorn (2008).

the idea of the existence of poverty convergence. Ravallion (2012, 507) argued that "countries starting out with a high incidence of absolute poverty should enjoy a higher subsequent growth rate in mean consumption and (hence) a higher proportionate rate of poverty reduction." However, Ravallion does not find evidence of proportionate poverty convergence in a sample of 90 developing countries.

In today's world, the bulk of poverty can be found in the developing world compared to developed countries.[2] The 80 percent of the poor are living in South Asia and Sub-Saharan Africa. Persistent poverty in developing countries can reduce the prospects of economic growth (Ravallion and Datt 1999). Poverty has many consequences both for a household and for broader society. It is a broader concept than just the absence of financial resources (Sen 1993, 2002). A household suffering from poverty loses human freedom, affecting children's schooling and social isolation, and increasing health-related issues. A poor household is not able to accumulate the human capital that, in turn, will affect the growth process of a country. An inadequate nutritional intake affects the productivity and work effort, which leaves a long-lasting impact on the economy. Ravallion (2016) argues that, along with income and health issues, social discrimination and exclusion, violence, and the fear of violence are parts of life. Poverty also creates a cost for the non-poor people such as crime, violence, diseases, and social disturbance.

Since the mid-1990s, poverty reduction and a higher living standard have become more important on the agenda of the national policy in less developed countries. The focus of developing countries has been on attaining the higher and sustained rate of economic growth to achieve the Millennium Development Goals (MDGs) of poverty reduction during the last two decades.[3] However, recently the development policymakers have also come to focus on income inequalities in sustainable development goals (SDGs).[4]

The assurance of equitable growth remains an uphill task in less developed and

[2]If we take a look at the statistics, the East Asia and Pacific regions have decreased poverty from 60.2 percent in 1990 to 3.50 percent in 2013. The South Asian region has reduced poverty from 44.6 percent in 1990 to 15.1 percent in 2013. Sub Saharan Africa has not performed well; its poverty rate is 41.0 percent compared to 54.3 percent in 1990 (World Bank 2016).

[3]The first MDG is the "Eradicate extreme poverty and hunger". Retrieve from https://www.un.org/millenniumgoals/.

[4]The United Nations Sustainable Development Goal 10 aims to reduce inequalities within and among countries. For more details on targets and facts, see http://www.un.org/sustainabledevelopment/inequality/.

developed countries in addition to both persisting and new development challenges. Besides a strong performance on poverty reduction, income inequality has increased in some parts of the world.[5] Persistent and high inequalities have hampered growth progress in some parts of the world (Ravallion 2016; Kanbur et al. 2014), especially in the Asian region (Balakrishnan et al. 2013). Moreover, inequality can slow down the effect of growth on poverty reduction. This effect is less fruitful in those countries where the distributional pattern of growth favors the non-poor (Bourguignon 2004) and in those countries who have a high level of initial inequality (Ravallion 1997, 2005).

Inequalities in income and wealth can also affect poverty through the misallocation of human capital resources. In the lower part of income distribution, households are not able to invest in human capital and will remain poor. A poor household has little incentive to invest in human capital because of low returns to education (Goenka and Henley 2013). This process creates a vicious circle, in which a household remains poor because it is poor. The widening gap between the lower and higher ends of income distribution may lead to a political backlash. This gap creates a pressure on governments to initiate policies which favors the bottom end of the income distribution in the short run and sustains the efficiency and growth in the long run (Alesina and Rodrik 1994). In view of these issues, the focus of political systems deviates from the economy. This is a widespread concern in less developed and developed countries alike (Kanbur et al. 2014).

A body of theoretical and empirical work has suggested that the initial conditions of a country matter for its growth prospects. The first strand of the literature demonstrates how initial inequality affects an economy's aggregate efficiency and output through restricting efficiency-enhancing cooperation and credit-market failures (Galor and Zeira 1993; Alesina and Rodrik 1994; Persson and Tabellini 1994; Birdsall et al. 1995; Clarke 1995; Perotti 1996; Benabou 1996; Perotti 1996; Aghion and Bolton 1997; Deininger and Squire 1998; Ravallion 1998; Bardhan et al. 2000; Knowles 2005).[6] The second strand of the literature explains that the size of the mid-

[5] The World Bank (2016) document that global income inequality slightly decreased from 40.1 to 39.3 between 1993 to 2008. It increased in East Asia and the Pacific, Industrialized countries, and South Asia. At the same time, it decreased in Sub-Saharan Africa, Latin America and the Caribbean, and Eastern Europe and Central Asia.

[6] Some literature did not support this fact, such as Li and Zou (1998); Barro (2000) and Forbes

dle class affects the growth process through fostering entrepreneurship, demanding high-quality goods, and institutional reforms (Acemoglu and Zilibotti 1997; Murphy et al. 1989; Birdsall et al. 2000; Easterly 2009; Sridharan 2004).

The third strand of the literature supports the opinion that it is the initial poverty that hampers the growth process in developing countries (Ravallion 2012). Ravallion explained that due to two distinct poverty effects, less developed countries do not experience such a quick and proportionate rate of poverty reduction. First, high initial poverty, at a given initial mean income, hampers subsequent growth rate, which is a direct effect of initial poverty. This poverty effect works against the mean convergence effect, such that a country with a higher level of initial poverty rate tends to experience a lower subsequent growth rate. Second, a higher incidence of poverty, at a given subsequent growth rate, is a handicap for the poverty-reducing effect of growth, which is an indirect effect of poverty. The size of the growth elasticity of poverty is lower in the country which has a higher initial incidence of poverty. Due to the higher initial incidence of poverty, the advantages of growth starting with a country's low initial mean income is lost in less developed countries.[7]

The literature has established strong links between poverty, inequality, and education. A high level of poverty and inequality is tied to low levels of educational outcomes and higher gender gaps in education in less developed countries (Filmer 2000). The education achievement gap is well recognized between poor and non-poor children. Children belonging to low-income families fall behind in test scores, enrolment and attendance rate and other measures of academic success (Carey 2002). Sen (2002) argues that insufficient education itself is a form of poverty. The accumulation of human capital in the form of education is not only a goal of its own, but is also a vital source to reduce future poverty (Dercon et al. 2007; Haughton and Khandker 2009). Levitan et al. (2003) argue that, among many other factors, poverty reduction is highly dependent on education. Inadequate financial resources reduce children's enrollment and attendance among the absolute poor in less developed countries. Investment in education is considered a vital indicator of reducing poverty and inequalities and promoting growth and prosperity, among many other

(2000).

[7]Ravallion (2009) and Lopez and Servén (2009) also explain how a country's growth path can rely on initial/current levels of poverty.

public investments. In developed countries, the children feel left out of the school community and social mainstream, due to relative poverty. In turn, this can affect their abilities and motivation to participate in education (Schnepf 2004). Education, poverty, and inequality are highly interconnected and need simultaneous attention from academic researchers and policymakers alike.

Education receives continuous attention in development policy debates in terms of easy access, equity and quality of education, and the allocation of more roles to local governments in education management and finance. Local autonomy is one of the key objectives of the World Bank's policies for strengthening the education systems by 2020 (World Bank 2011). Proponents of education decentralization[8] argue that decision-making in delivery services of education which is closer to the local people and at the lower tier of governments might improve educational outcomes and achievements (Fiske 1996; Hanson and Ulrich 1994). During the last decade, researchers and policymakers have focused on quality education (test score), instead of simply focusing on the quantity of education (enrollment and attendance). An extensive literature is now available that argues that the quality of education promotes the process of sustained economic growth and poverty reduction (Barro and Lee 2001; Hanushek and Kimko 2000; Hanushek and Wößmann 2007 and Hanushek and Zhang 2006).

Improvement in education quality is the top priority for the global human development agenda in less developed countries (United Nations 2015).[9] National governments, international donors, and households spend over a hundred million dollars annually on education (Filmer et al. 2018, Glewwe and Muralidharan 2016). Despite this significant spending, little is estimated on how this spending has increased the years of schooling and the skills that students acquire. Even though enrollment of students increases over time in developing countries, the quality of education is often low.

The world has made a considerable expansion in education historically. The main share of global literacy comes through increasing the enrollment in primary

[8]At the most basic level, decentralization refers to the devolution of fiscal and decision-making powers to the local government from the central government.

[9]Sometimes countries face a tradeoff between quality and quantity of education because the fast expansion in education results in lowering the education quality. In such cases, the struggle goes on improving the education quality, while the effect of education on poverty may be small.

education. However, secondary and tertiary education have also seen impressive growth. Despite all the improvements, some countries/regions are still lagging in educational outcomes (Roser and Ortiz-Ospina 2016). If we take a look at the South Asian region, the educational achievements differ across the goals and targets as well as across and within countries. The net secondary enrolment of South Asia is 59 percent in 2014, which lags behind the world average of 65 percent. In Pakistan, girls and students from lower social-economic backgrounds have lower access to primary education (Kumar et al. 2016). The quality of education is often poor, especially in rural and remote areas. The low educational achievements in South Asia are explained by low public education expenditure as a percentage of GDP. For example, the share of education expenditure as a percentage of GDP ranges from 2.0 percent in Bangladesh to 3.9 percent in India, 2.5 percent in Pakistan, and 1.7 percent in Sri Lanka. All countries of South Asia are spending well below the threshold of 6 percent of GDP.[10] Moreover, it is recommended that Pakistan should spend at least 7 percent of its GDP on education (Government of Pakistan 2009).

If we take an in-depth look at these expenditures, we find that the share of the non-salary budget is only 12 percent in Pakistan's total education budget. The situation is even worse in Punjab-Pakistan, where the share of non-salary expenditure is only 3 percent in comparison with 86 percent and 11 percent of salary and the developmental education budget (I-SAPS 2015).

The South Asian region embarked on the path of economic development around the middle of the 20$^{\text{th}}$ century. All countries in South Asia shared some common initial conditions and economic fundamentals and a historical legacy of British colonial rule for nearly two hundred years. Given the economic progress and poverty reduction which has taken place during the last two decades, the South Asian region constitutes an important case study to analyze poverty reduction and income inequality. The focus of this dissertation is at the subnational level of the two most populous countries in South Asia, namely India and Pakistan. The first two essays are based on Indian and Pakistani data, while the third essay considers only Pakistan's subnational level.

A subnational analysis is needed for the following reasons. First, there is a grow-

[10] See the Oslo Declaration: https://en.unesco.org/themes/education/.

ing interest in analyzing subnational poverty and inequality for development planning. A subnational analysis of poverty convergence and inequality convergence is helpful for understanding the associations between changes in poverty and inequalities with their respective initial conditions. In the absence of poverty convergence across the globe, there are more chances to observe it at the subnational level. The reason for this is that national governments are more familiar with their poor and lagging regions, and governments can start targeted anti-poverty programs. India and Pakistan have both started targeted anti-poverty programs so that one can expect a faster pace of poverty reduction.[11] Second, the subnational analysis provides a set of guidelines for the development policymakers and national governments to ascertain whether this region is on track to reduce the regional imbalance (by reducing poverty and inequality). This dissertation also highlights the progress towards SDGs.

This dissertation attempts to contribute to the literature by providing the subnational picture of poverty reduction, inequality, and educational decentralization in India and Pakistan. The main ideas, arguments, and implications of each of the essays are summarized below.

A subnational analysis of poverty convergence: Evidence from India and Pakistan

The world reduced levels of poverty to 10.7 percent in 2013 compared to 35 percent in 1990 (World Bank 2016). South Asia decreased poverty from 44.6 percent in 1990 to 15.1 percent in 2013. The regional average of poverty rates in South Asia was 40.7 percent in the late nineties. India and Pakistan introduced some anti-poverty programs for lagging regions/districts, whose objective may imply regional poverty convergence in two countries. In the first essay, entitled "A subnational analysis of poverty convergence: Evidence from India and Pakistan", I analyze the subnational patterns of changes in poverty within the framework of poverty convergence pioneered by Ravallion (2012). I also analyze the two distinct effects of poverty at the subnational level in India and Pakistan, e.g., direct and the indirect poverty effects.

Since the earlier literature on poverty convergence does not consider the rural

[11] For example, Rashtriya Sam Vikas Yojana (RSVY), National Food for Work Programme (NFFWP), Backward Regions Grand Fund (BRGF), Pakistan Poverty Alleviation Fund (PPAF), Punjab Economic Opportunities Program (PEOP), Benazir income support program (BISP).

and urban disaggregation, I extend the convergence analysis to rural and urban sectors. Most of the population is living in rural areas in less developed countries, so it might be thought that rural or urban convergence effect dominates the total effect of convergence within a country. This essay takes seriously the issue of measurement error with a novel strategy. I use consistent adjusted least square estimation accounting for measurement error, unlike the instrumental variable which is used in Ravallion (2012) and Ouyang et al. (2019). This method is useful when initial variables are measured with error or noise. The measurement error in initial poverty implies that the convergence coefficient is subject to attenuation bias, and it might be the case that this overestimates convergence (Asadullah and Savoia, 2018). Furthermore, I also use the standard growth-based regression to compare my results with the estimation of consistent adjusted least squares.

In order to analyze poverty at the subnational level, I explore two household surveys in this study. I use the National Sample Survey (NSS) data in the case of India, which covers a diverse range of socio-economic aspects and all the geographical regions. I focus my analysis on the districts of 17 major states of India, as these states are politically and economically more stable than the rest of India. I use two rounds of Multiple Indicator Cluster Survey (MICS) data in the case of Punjab-Pakistan. The MICS is a large data set that is representative at the district level for measuring the mean consumption and poverty. In the case of Pakistan, this study focuses only on the Punjab province. The reason for this is that Punjab is the largest province of Pakistan, covering 55 percent of the population, and it has a nice data set in terms of MICS.

I present five main sets of results. First, I do not find any evidence of mean consumption convergence and proportionate poverty convergence at the national level in India. However, I find convergence clubs in mean consumption and poverty at the state level in India. The speed of poverty convergence is faster than the mean consumption in India. This could be because the initially poor districts are worse in exploiting the growth for poverty reduction, even though the initially poor districts grow faster conditionally on initial mean consumption. I find the same pattern of results when the analysis is disaggregated at the rural and urban levels. Second, the evidence offers support for mean consumption convergence and poverty convergence in the case of Punjab-Pakistan. The magnitude of mean consumption convergence and poverty convergence are the same, in accordance with the framework of Ravallion (2012). Third, in India, the significance of proportionate mean consumption convergence is changing when one takes into account measurement error. In Punjab-Pakistan, the convergence magnitudes are more modest after accounting for the measurement error. Fourth, I do not find any direct adverse effects of poverty on the subsequent growth rate in the two countries. Fifth, I find evidence of indirect poverty effect in the overall districts of India. I interpret that the two distinct poverty effects do not neutralize the advantages of backwardness and advantages of growth. The patterns of results are different from the pioneering work of Ravallion (2012). In both countries, the absolute poverty convergence shows that the poverty rate in poor areas decreases more quickly in absolute terms than in affluent areas. The speed of poverty convergence is higher in Punjab-Pakistan when compared to India. This may be due to the fact that Punjab-Pakistan is a small and homogeneous region, and that it is not as diverse as India.

The contribution of this study is as follows. First, this essay initiates an academic debate that, to the best of my knowledge, it is necessary to analyze poverty convergence within a country, rather than between countries. Second, this essay contributes to the discussion of poverty convergence clubs. Third, I think that the strengths of my analysis are to take the issue of measurement error with a novel approach seriously. Fourth, this study initiates a policy debate regarding whether these countries are presently on track to reduce poverty and their regional imbalance. The absolute poverty convergence shows that both countries are on track to reduce poverty. However, the pace is slow to meet the SDGs.

A subnational analysis of inequality convergence: Evidence from India and Pakistan

While the first essay analyzes the poverty convergence at the subnational level, in the second essay, entitled "A subnational analysis of inequality convergence: evidence from India and Pakistan," I investigate whether the income inequalities are persistent overtime at the subnational level in India and Pakistan. Growing inequalities are not helpful for any country or region as they create sociopolitical instability and conflict. The social and economic pitfalls of inequalities are harsher in developing countries than in developed countries (Hirschman and Rothschild 1973; Easterly 2007; Wei and Kim 2002; Thorbecke and Charumilind 2002; Gruen and Klasen 2008; Østby et al. 2011; Fjelde and Østby 2014; Ostry et al. 2014; Dabla-Norris et al. 2015). Based on this discussion, in this paper I seek an answer to the question whether income inequalities are persistent over time or whether they converge at the subnational level in India and Pakistan.

To examine inequality convergence, the focus of this essay is to use the consistent adjusted least squares estimation for accounting the measurement error. While measuring and analyzing inequality, the previous literature highlights the issue of measurement error in cross-sectional data. Besides the consistent adjusted least squares regressions, I also report the ordinary least square results to highlight the difference between magnitudes and as a robustness check. For this purpose, I used two household surveys. In the case of India, I use the 61^{st} and 68^{th} rounds of NSS data. I only consider the districts of 17 major states of India. These states cover 88% of the total population of India, and they are both politically and economically more stable compared to the rest of the country. In the case of Pakistan, I use the first and third rounds of MICS data. I consider only the Punjab province instead of the whole of Pakistan.

The results of this chapter are as follows. I find that inequality increased in two countries based on the Theil index and the Gini coefficient. Second, I find evidence of inequality convergence (proportionate convergence and absolute convergence) in two countries. Third, the significance of the convergence coefficient does not change much by accounting the measurement error. The measurement error can be a serious threat to the validity of convergence if the convergence coefficient is near zero. I find that, by accounting for the measurement error, the convergence coefficient goes down in the range of 17–38 percentage points in different specifications.

Moreover, these findings are not sensitive to other measures of inequality (mean logarithmic deviation and coefficient of variation). Being the two most populous countries in the South Asian region, this essay will provide a guideline for development policymakers to ascertain whether this region is on track to reduce income inequalities. By considering the current speed of absolute inequality convergence, both countries will significantly improve the gap between poor and rich by the end of SDGs 2030.

School grants and educational outcomes: The impacts of a non-salary budget reform in Punjab-Pakistan

In the third and last essay, entitled, "School grants and educational outcomes: The impact of the non-salary budget reform in Punjab-Pakistan" co-authored with Min Xie, we study the effects of reform on education outcomes and achievements. We analyzed a decentralized school grant for public schools and address two questions. First, does the provision of a decentralized grant affect the school's human capital (measured by teacher's attendance rate) and the school's physical infrastructure? Second, does this decentralized grant improve education outcomes and achievements?

We examine the effect of non-salary budget reform (NSB) reform in Punjab-Pakistan. Before NSB, the public school in Punjab province receives a fixed grant annually, irrespective of the school's needs and priorities. Each primary and secondary school receives Rs. 20,000 and Rs. 40,000 respectively every year. This fixed grant is inadequate to maintain the school's basic facilities (such as a functional toilet, sanitation, drinking water, and boundary walls). A rough estimate to cover these necessary expenditures are Rs. 70,000.[12] To overcome this low funding situation in public schools, the Government of Punjab initiated the NSB reform in 2013. Under this reform, expenditures are now calculated based on a need-based formula instead of a fixed based rule. One of the key elements of NSB is the devolution of financial decision-making to the school councils. The school council consists of teachers, parents, and notable community members who are responsible for managing and spending these funds. The amount under NSB reform increased by about ten times compared to the fixed allocation rule. The NSB reform was rolled out in three phases. For phase one, nine districts were selected in 2013. In 2014, an additional nine districts were selected. In 2015, the reform was implemented in the whole province.

In this work, we adopt the difference-in-differences method to estimate the reform's impact. The NSB's staggered roll-out schedule has created temporal and

[12]These expenditures are calculated on the basis of field interviews with school teachers, head-teachers, community members, members of the teacher's union, and some members from the education department across all the divisions of Punjab.

geographical variations in policy treatment, which we exploit to estimate the reform's impacts. This identification strategy of NSB reform delivers the average effects of entering the NSB reform. We collect data from various sources. We collect administrative data on the schools' financial accounts and infrastructure conditions, the student's test scores, and student and teacher attendance from the School and Education Department of Punjab and the Punjab examination commission. We use the data of children's enrollment and students' reading ability and mathematical ability scores from Multiple Indicator Cluster Survey (MICS) and Annual Status of Education Report Pakistan (ASER). Both are independent household surveys.

We find four sets of findings. First, the school's annual income and expenditure increased by Rs. 180,000 and Rs. 135,000, respectively, after the NSB reform. Second, the condition of infrastructure is improved significantly due to this reform. Improvements are found in existing infrastructure such as complete boundary walls, the fraction of functional toilets, and the school building's condition. Moreover, in terms of human capital, the school's condition is improved as we find a slight increase in the attendance of teachers. Third, we do not find any effects of reform on students' enrollment and attendance rates. Fourth, in terms of students' achievements, we do not find any impact on the students' test and ability scores.

We explain the lack of policy effects on educational outcomes in two ways. First, the lack of policy effects is due to the school council's inadequate capacity. A report on Punjab's education sector procurement explains that the majority of the school council members do not understand the procedure of the procurement rule of the grant and financial management (I-SAPS 2014). Second, the school council does not have enough administrative authority to hold teachers accountable. Based on the teachers' performance, the school council cannot fire the teacher, and teachers also have political and union patronage. Without the accountability of teachers, increasing the funding may not be very effective for students' achievements. Moreover, the finding of this chapter is consistent with Beasley and Huillery (2017) and Mbiti et al. (2019). They explain that the effectiveness of decentralized school grants depends on the capacity of local community members who are responsible for grant management.

This study is related to the literature on decentralized school grants and their impact on educational outcomes and achievements in less developed countries. The empirical literature is limited, very recent, and mostly based on small scale randomized controlled trials (RCTs). From this limited empirical literature, we abstract three lessons. First, the school-based management (teachers, parents, and other community members) should be supported in order to maximize the use of their efficient management skills and fiscal decisions that are likely to improve the school's output.[13] Second, the impact of a decentralized school grant may be affected by the stakeholders' behavioral responses.[14] Third, improving human capital (spending on teachers' welfare and human resource training) seems to bring about effective results.[15] The contribution of this chapter is three-fold. Firstly, this study adds some evidence to the limited and very recent literature on the decentralized school grants and students' achievements. Secondly, we evaluated a real and large-scale policy that can capture a real-world effect instead of the short-term effect of RCT. Thirdly, this chapter sheds light on Punjab-Pakistan's progress in achieving the goals and targets of SDGs. SDGs set multiple goals and targets related to education. All their goals are related to our findings, such as equal access to education, gender equity, equitable quality education, conducive learning environments, and the adequacy of trained teachers.

[13] For details, see Blimpo et al. (2015) and Beasley and Huillery (2017).
[14] For details, see Das et al. (2013) and Andrabi et al. (2020).
[15] For details, see Carneiro et al. (2020) and Beasley and Huillery (2017).

Chapter 2

A Subnational Analysis of Poverty Convergence: Evidence from India and Pakistan

Abstract This study revisits poverty convergence at the subnational level in India and Pakistan by using household data. I find evidence in favor of poverty (proportionate) convergence clubs at the state level in India. In contrast, I do not find evidence in favor of poverty (proportionate) convergence at the national level in India. In the case of Pakistan, I observe the evidence in favor of poverty convergence. This study finds that the rate of consumption convergence and proportionate poverty convergence is very similar at the subnational level in Pakistan and in India's rural districts. The districts with a high initial incidence of poverty appear to grow faster, leading to poverty convergence in two countries. The structure of India's and Pakistan's growth is different from the rest of the developing world, in that high initial poverty is the leading cause of the absence of poverty convergence. However, the speed of poverty convergence is too slow to meet the desired target of SDG's 2030 regarding poverty reduction in India and Pakistan.

2.1 Introduction

According to a recent update by the World Bank (2016), 10.7 percent of the world population were living in extreme poverty in 2013 compared to 35.0 percent in 1990. East Asia and the Pacific regions reduced their poverty rate from 60.2 percent in 1990 to 3.50 percent in 2013. The pace of poverty reduction in Sub-Saharan Africa is slow; the level of poverty shrank from 54.3 percent in 1990 to 41.0 percent in 2013. While at first glance the numbers of poverty reduction globally look inspiring, upon a closer review, the picture is poor for South Asia. The South Asia region decreased its poverty rate from 44.6 percent in 1990 to 15.1 percent in 2013. Despite performing well in poverty reduction by dropping 29.5 percentage points, South Asia accounted for the second-largest share of world poverty between 1990 to 2013. South Asia's share of the poor increased from 27 percent to 33 percent between 1990 to 2013, while the total number of poor people fell by 248 million. While the poverty rate in South Asia was 13 percent in 2013, this poverty rate is still significantly higher than in Central Asia, East Asia and the Pacific, Eastern Europe, and Latin America. Still, around 80 percent of the extremely poor people are living in South Asia and Sub-Saharan Africa. The regional average of poverty rates in South Asia was 40.7 percent in the late nineties.[1] At the regional level, most of the indicators show a path towards poverty reduction across central India, eastern and southern Pakistan, northern and southeastern Bangladesh and western Nepal. However, there are pockets of improvement for poverty reduction in this region. Most of the poor still live in rural areas in South Asia, while better opportunities are available in cities and towns. From this evidence it is clear that the patterns in levels of poverty and the pace of poverty reduction require specific attention from policymakers, especially in South Asia.

In South Asia, poverty reduction and reduction of regional imbalance are the key concerns for policymakers. To reduce the regional imbalance, the Indian government has initiated anti-poverty policies for specific regions/districts. The Planning commission of India has initiated the Rashtriya Sam Vikas Yojana (RSVY), National Food for Work Programme (NFFWP), and Backward Regions Grand Fund (BRGF)

[1]The highest poverty rate has been observed in India (44.2 percent), while Sri Lanka has the lowest percentage of poor people (6.6 percent) in South Asia. The poverty rates in other countries of this region were 36 percent in Bangladesh, 37.7 percent in Nepal, and 31 percent in Pakistan.

for the backward districts in order to eradicate poverty in these areas. Besides India, Pakistan has also made many efforts to reduce poverty and regional imbalance within and across the provinces. The Pakistani government has initiated many programs to eliminate poverty such as Pakistan Poverty Alleviation Fund (PPAF), Pakistan bait-ul-mal (PBM), Benazir income support program (BISP), Waseela-e-Haq and some microfinance initiatives. The Punjab province of Pakistan also introduced Punjab Economic Opportunities Program (PEOP) to reduce regional disparities by focusing on the poor districts in Punjab province. As India and Pakistan introduced some anti-poverty programs for lagging regions/districts, the objectives of those policies may lead to regional poverty convergence in both countries.

In this study, I am focusing on the two most populous countries of South Asia, namely India and Pakistan. The economic growth in India picked up speed after the economic reforms in 1990, but the nature of its growth is unbalanced. Many studies find that regional income disparities are on the increase in India, since richer states are growing faster compared to poor states (Bardhan 2012; Cashin and Sahay 1996; Rao et al. 1999; Trivedi et al. 2003; Bandyopadhyay 2004; Das 2012; Ghate and Wright 2012; Bandyopadhyay 2012; Das et al. 2015). However, Ahluwalia (2000) argues that the gap between rich and poor states decreased after the economic reforms. This concern about regional disparities in development was expressed in the Indian government's strategies. So, the central objective of the Eleventh Five-Year Plan (2007-12) promoted faster and more inclusive growth. In Pakistan, regional poverty/disparity is relatively ignored and very few studies are available (Jamal and Khan 2003; Zaidi 2015). Both countries have taken efforts to reduce poverty and reduce the regional imbalance, but still there is poverty and regional disparities.

In this essay, I assess the subnational patterns of changes in poverty within the framework of poverty convergence pioneered by Ravallion (2012). Moreover, I analyze the two distinct effects of poverty at the subnational level in India and Pakistan. First, I look at the direct poverty effects, asking whether initial poverty predicts a slower subsequent growth rate. Second, I look at the indirect poverty effects, asking whether poverty is a handicap for the poverty-reducing effect of growth.

A few studies examine poverty convergence across less developed countries, but the empirical results are inconclusive (Ravallion 2012; Azevedo et al. 2016; Cuaresma et al. 2017; Ouyang et al. 2018; Asadullah and Savoia 2018; Ouyang et al. 2019). In a seminal paper on poverty convergence, Ravallion (2012) shows that countries which begin with a higher rate of poverty tend to attain relatively lower rates in poverty reduction. In a sample of 90 countries, Ravallion did not find any evidence in favor of proportionate poverty convergence. He argues that two distinct poverty effects counterbalance the mean convergence effect. On the one hand, a direct adverse effect of poverty restricts the process of economic growth, with the outcome that countries starting with higher initial poverty rates grow more slowly. On the other hand, an indirect effect of poverty dampens the impact of growth on poverty. A high initial incidence of poverty makes it harder to achieve a higher proportionate impact on poverty through economic growth. These two poverty effects neutralize the advantage of backwardness and the advantages of growth, leading to an absence of poverty convergence in the developing world. Cuaresma et al. (2017) do not observe any evidence of proportionate poverty convergence based on the data of Ravallion (2012). They noted the little evidence of poverty convergence when they removed outliers by controlling for transition economies. Ouyang et al. (2018) find the presence of proportionate poverty convergence in the region of Sub-Saharan Africa and few regions in Ethiopia and Rwanda. Asadullah and Savoia (2018) observe evidence of absolute poverty convergence across the developing countries.

There is no evidence available for regional poverty convergence in Turkey after the financial crisis (Azevedo et al. 2016). In contrast, these authors document the presence of poverty convergence before the crises. Ouyang et al. (2019) do not notice any evidence of proportionate poverty convergence across developing countries. However, they find it present in Sub-Saharan Africa.

A few studies are available in the literature that find the lack of proportionate poverty convergence across less developed countries. Moreover, only one study is available, to the best of my knowledge, which examines within-country proportionate poverty convergence. There is not any study available, which examines the absolute poverty convergence at the subnational level. None of the studies found the poverty convergence club. Azevedo et al. (2016) cannot do it at the subnational level in Turkey due to the sample size. Ouyang et al. (2019) similarly did not find any evidence of the poverty convergence club across developing countries.

This study employs Ravallion's (2012) framework to analyze poverty convergence at the subnational level in India and Pakistan. Methodologically speaking, the innovation of this study is that I take seriously the issue of measurement error by using an empirical strategy which is thus far unexploited in the empirical convergence literature. Temple (1998) highlights the problem I address: in a simple growth regression, where a country's per-capita GDP growth rate is regressed on the logarithm of its initial per-capita GDP, measurement error in initial GDP per capita will result in an attenuation bias of the slope coefficient and systematically underestimate the β convergence coefficient. This implies detecting convergence patterns when in fact there are none. Along these lines, he argues that the convergence-rate estimates in Mankiw et al. (1992) are highly sensitive to such measurement error and might in fact be spurious. Arguably, this problem is even more severe in poverty convergence regressions (see e.g., Asadullah and Savoia, 2018) – when poverty rates are measured with a greater error than fundamental national account statistics. My approach to estimating convergence coefficients consistently in the presence of such threats unfolds as follows. Since I estimate all consumption and poverty statistics which enter the convergence regressions from household survey data in a first step, I am able to assess the quantity of the unsystematic measurement error of poverty rates as well as consumption averages by their respective sampling errors. I then use so-called consistent adjusted least squares regression (Wansbeek and Meijer, 2000), which employs the signal-to-noise ratio of poorly measured regressors as additional input, to obtain consistent estimates of the slope coefficient of interest in the convergence regressions. Comparisons of the resulting estimates with standard, not adjusted convergence regression estimates show that accounting for measurement error has some, albeit not a large effect on the estimated convergence patterns in my applications.

I use two data sets in this study. I am comparing the much-explored data of the National Sample Survey (NSS) in the case of India and the much less explored data of the Multiple Indicator Cluster Survey (MICS) in the case of Punjab-Pakistan. In the case of India, I use two rounds of NSS data. The NSS is a household survey which covers a diverse range of socio-economic aspects and all the geographical regions. The focus of analysis lies on the districts of 17 major states of India. The population share of the 17 major states constitutes almost 88 percent of the total population of India. Therefore, I can generalize my result to the entirety of India.

Besides India, in order to measure mean consumption and poverty at the micro-level, Pakistan has faced the challenge of the scarceness of data. Regional poverty studies are not available, to the best of my knowledge, at the district level in Punjab-Pakistan because the available households' surveys do not have sufficient regional identifiers. That is why Pakistan gives less attention to analyzing the spatial pattern of poverty, even though Pakistan has had severe poverty traditionally. This study focuses on the province of Punjab-Pakistan for two reasons. Firstly, it is the largest province of Pakistan in terms of its population. The total population of Punjab is 110 million (53 percent of the total population of Pakistan), according to the population census of 2017. The economy of Punjab contributes significantly to the overall economy of Pakistan. It contributes 55 percent of Pakistan's total production of goods and services. The performance of Punjab's economy moves in tandem with Pakistan's economy. In 2005-06 the growth rate of Punjab and Pakistan was almost 5.8 percent. During 2011-12, the Punjab growth rate is 5 percent, while Pakistan's growth rate is 4 percent. The poverty of Pakistan was 35 percent in 2007-08 and 27 percent in 2013-14, while poverty in Punjab was 32 percent in 2007-08 and 21.90 percent in 2013-14. Punjab lies below the average poverty rate of Pakistan. These figures reveal that Punjab closely represents the picture of Pakistan as a whole.

Secondly, two rounds of Multiple Indicator Cluster Survey (2003 & 2011) are available in Punjab to measure the mean consumption and poverty at the districts level. The MICS is a large data set that is representative at districts level. Generally, Pakistan does not have this type of data coverage. Other micro data sets are available in Pakistan such as the Pakistan social and living standard measurement (PSLM) 2005-06 & 2010-11 and the household integrated and economic survey (HIES) 2004-05 & 2010-11. The PSLM has a sample size of around 70,000 households which covers all the districts from Pakistan, but PSLM does not cover the consumption indicator to measure the mean consumption and poverty. However, HIES covers the consumption indicators, but it is only representative at the provincial level with a total sample of around 15,000 households. The MICS has superiority over these two data sets. It has not only the consumption indicators but is also representative at the district level.

I also disaggregate the analyses by rural and urban sectors. Since most of South Asia's population is living in rural areas and growth and poverty patterns have differed markedly across those sectors, I explore the possibility that rural or urban divergence or convergence drives the overall divergence or convergence patterns. Alternatively, convergence or divergence between these two sectors could drive the overall patterns.

I have five sets of results. First, in the case of India, I do not find any evidence of convergence, either in mean consumption or in poverty at the national level. However, I find convergence clubs at the state level in mean consumption and proportionate poverty. The speed of convergence in consumption and poverty is slower in India than in Punjab-Pakistan. Nevertheless, I find that the speed of poverty convergence is faster than the speed of mean consumption convergence in India. The reason for this might be that initially poor districts are worse in exploiting the growth for poverty reduction, but initially poor districts grow faster conditional on initial mean consumption. When the analysis is disaggregated at the rural and urban levels, this study also finds convergence clubs. In the rural districts of India, this study finds proportionate poverty convergence and mean consumption convergence of the same magnitude, in accordance with Ravallion's (2012) simple accounting framework. Second, in the case of Punjab-Pakistan, I observe the evidence in favor of mean consumption convergence and poverty convergence. Evidence in favor of mean consumption convergence and poverty convergence is also observed in rural and urban districts of Punjab-Pakistan. I find poverty and consumption convergence of the same magnitude.

Third, while using the consistent adjusted least squares, the significance of proportionate poverty convergence and mean consumption convergence changes at the national level in India. However, at the state level in India and Pakistan, the convergence coefficients of consistent adjusted least squares are slightly more modest, but not by much. Fourth, I do not find any direct adverse effect of poverty in India and Punjab-Pakistan. In two countries, high initial poverty is helpful in increasing the growth of mean consumption. Fifth, the result indicates the presence of indirect poverty effects in overall districts of India. However, I do not identify the regression results in the case of Punjab-Pakistan. These results illustrate that the two poverty adverse effects do not neutralize the "advantages" of backwardness and the "advantages" of growth. The patterns of my results are different from Ravallion (2012). He observed that the two poverty effects neutralize the mean convergence property and growth elasticity, so that there is no proportionate poverty convergence across less developed countries.

This study contributes to the existing literature in the following ways. First, to the best of my knowledge, this study initiates an academic debate about why it is important to analyze the poverty convergence at the subnational level compared to the global level. Despite the absence of proportionate poverty convergence in less developed countries, there are many reasons to seek the presence of convergence at the subnational level. Firstly, the respective government of a country is more familiar with the lagging and poor regions. Therefore, the national governments are in a better position and possess the ability to start and implement the specific poverty reduction policies in a targeted manner. Secondly, the regions/districts within a country are more linked and there exists freer movement of labor and goods compared to the movement between countries. These are the potential reasons that poor regions/districts grow more quickly compared to rich regions/districts. Moreover, doing a subnational analysis of poverty convergence is helpful for a more comprehensive understanding of the relationship between poverty reduction and growth rate in the developing world. It will provide extra incentive for national governments to design and implement pro-poor policies. Second, this study contributes to the discussion of poverty convergence clubs. In the previous literature, the greater focus has laid on mean convergence clubs and to a lesser extent on poverty convergence clubs. Azevedo et al. (2016) cannot show poverty convergence clubs at the subnational level in Turkey, while Ouyang et al. (2019) did not find any evidence of poverty convergence clubs across the less developed countries. I find evidence in favor of the existence of poverty convergence clubs at the state level in India.

Third, I think that the strength of my analysis is to take seriously the issue of measurement error with a novel approach. I use consistent adjusted least squares, which is also applicable to other empirical convergence analyses. While using the consistent adjusted least squares, the significance of mean consumption convergence has changed at the national level in India. However, at the state level in India and Punjab-Pakistan, the convergence coefficients are slightly more modest by using the consistent adjusted least squares.

Fourth, this study starts a policy debate regarding the question whether these countries are on track in their poverty reduction generally and in reducing the regional imbalance. The absolute poverty convergence shows that both countries are on track in reducing poverty, but the pace is slow. With the current speed of convergence, India will have a poverty rate of 8 percent in 2030, while Punjab-Pakistan will have 17 percent. In two countries, absolute poverty convergence shows that poverty rate decreases faster in poor areas than in affluent areas. In India, regional disparities remain present across the states but are on the decrease within states. That is why cross-state disparities are persistent and dominate within-state convergence. One of the reasons for convergence clubs is the difference in the extent of policy reforms by states during the post-reform period. Some states have implemented key reforms in specific sectors, while others have lagged behind in initiating economic reforms. Bajpai and Sachs (1999) distinguish between three categories of states based on implementing the reforms: (i) reform-oriented states, (ii) intermediate reformers, and (iii) lagging reformers. In India, the government policies which aimed at the reduction of regional disparities have been moderately effective within states but were not able to mitigate disparities at the national level. Besides this, Punjab-Pakistan is a small and homogeneous region which is not as diverse as India. I cannot report about the whole of Pakistan, but I suspect that I would find similar results about the failure of convergence at the national level as in India.

The rest of the study is organized as follows. In section 2, I review the conceptual framework of proportionate poverty convergence as proposed by Ravallion (2012) and the concept of absolute poverty convergence as proposed by Cuaresma et al. (2017). In section 3, I discuss the empirical approach. I describe the data in section 4. Section 5 presents the results of consumption convergence and poverty convergence. Finally, section 6 presents a conclusion.

2.2 Conceptual Framework

Ravallion (2012) initiates the discussion on the concept of proportionate poverty convergence. He states that there should be convergence in poverty due to the two stylized facts of development economics, i.e., an "advantage" of backwardness and advantages of growth. A country always has room to achieve a high rate of economic growth if it has a low level of income initially. The equation (2.1) in the following is for the identification of the first stylized fact "advantages of backwardness" and mean income (consumption) convergence.

$$\Delta ln\mu_{it} = \alpha_i + \beta_i ln\mu_{i,t-1} + \epsilon_{it}, \tag{2.1}$$

Where $\mu_{i,t}$ is the mean income (consumption) in the country i and time t, α_i is the country-specific effects, and ϵ_i is the zero-mean disturbance term. The coefficient of β_i is the convergence rate. If the estimated value of β_i is negative and statistically significant, then unconditional convergence in consumption at the rate of β_i takes place. The second stylized fact is the "advantage of growth." A higher level of mean income leads to a reduction in poverty. In equation (2.2), a log-linear relationship between poverty and mean consumption depicts the advantage of growth.

$$lnH_{it} = \delta_i + \eta_i ln\mu_{it} + \nu_{it}, \tag{2.2}$$

Where H_{it} is the absolute poverty rate in the country i and time t, δ_i is the country-specific effects, and ν_i is the zero-mean disturbance term. The coefficient of η_i is assumed to be < 0, as a higher mean income (consumption) is supposed to reduce poverty. Equation 2 also explains the growth elasticity of poverty to mean consumption, as explained by Bourguignon (2003). According to Ravallion (2012), both of these stylized facts imply that "countries starting-out with a high incidence of absolute poverty should enjoy a higher subsequent growth rate in mean consumption and (hence) a higher proportionate rate of poverty reduction." More reliable and stronger results are obtained if log-linear models use for mean income/consumption and poverty. Ravallion (2012) states that equations (2.1) and (2.2) imply the growth model for poverty convergence. The poverty convergence equation (2.3) can be derived by solving equations (2.1) and (2.2).

$$\Delta lnH_{it} = \alpha_i^* + \beta_i^* lnH_{i,t-1} + \epsilon_{it}^* \quad (2.3)$$

Where $\alpha^* = \alpha_i\eta_i - \beta_i\delta_i$, $\epsilon_{it}^* = \epsilon_{it}\eta_i + \nu_{it} - (1+\beta)_i\nu_{it-1}$ and $\beta_i^* = \beta_i$. A negative and statistically significant β_i^* indicates unconditional poverty convergence, i.e., if initial poverty drops by one percent, the rate of poverty reduction would increase by β_i^* percent. Equation (2.3) gives the estimates of unconditional poverty convergence. Adding some additional explanatory variables gives the estimates of conditional poverty convergence. One exciting feature in equation (2.3) is the equal rate of coefficients $\beta_i^* = \beta_i$. Ravallion (2012) argues that mean consumption and poverty have the same rate of convergence, even though he does not find any empirical evidence for poverty convergence. By using the household level data of 90 countries, Ravallion (2012) finds evidence of convergence in household mean income, but he does not find evidence of proportionate convergence in poverty. He explains this by the fact that a relatively poor household is more likely to be credit-constrained and has not enough resources for investment. If a household is under or close to the poverty line, it is more difficult for it to save and invest its money than a household who is above the poverty line. In short, Ravallion (2012) explains that initial poverty itself restricts poverty convergence. Ouyang et al. (2019) do not find evidence of proportionate poverty convergence across the countries while finding it in Sub-Saharan Africa. They also find that initial poverty no longer slows down the subsequent growth when they control for other variables in the extended sample. Ouyang et al. (2018) find the proportionate poverty convergence in 90 less developed countries after controlling country fixed effects. Similar results are also found for the data from four rounds of the survey of Ethiopian regions and districts in Rwanda between 2000 and 2010.

Cuaresma et al. (2013) revisit the Ravallion (2012) findings on why countries starting out at high poverty rates do not perform well and enjoy less poverty reduction. They highlight the importance of macroeconomic volatility in the process of poverty reduction. They find evidence of proportionate poverty convergence among countries with a low level of macroeconomic volatility. If the volatility level of a country exceeds its threshold level, it no longer converges in terms of poverty. Ouyang et al. (2019) do not find any evidence of poverty convergence in 104 less developed countries during 1980-2014. They argue that the initial poverty nullifies the effectiveness of growth in poverty reduction explains the lack of poverty convergence. When they split the Sub-Sahran Africa (SSA) sample, they find evidence of poverty convergence in SSA. In SSA, they do not find any adverse direct poverty effect.

Cuaresma et al. (2017) criticize the concept of proportionate poverty convergence in twofold.[2] First, the equation of proportionate poverty convergence does not fully capture the concept of welfare. A substantial change in ΔlnH_{it} does not imply an equally large change in the welfare of $lnH_{i,t-1}$. Second, the term η_i in equation (2.2) shows that the relationship between the dependent and independent variable is heterogeneous (Klasen and Misselhorn (2008)). Klasen and Misselhorn (2008) criticize the growth elasticity of poverty given by Bourguignon (2003). They explain that proportionate poverty changes cannot be calculated when the headcount ratio is zero at the start or the end of the period. The changes in proportionate poverty can be substantial when the incidence of poverty is very small, e.g., a change by 2 percent to 1 percent result is a 50 percent reduction in the headcount ratio. The formula to measure the elasticity of poverty captures the marginal changes; they cannot be applied when there are large changes in poverty incidence. Third, generally, policymakers are interested in the 'percentage reduction' in poverty rather than the 'percent reduction' in poverty. So, policymakers prefer to use the absolute poverty rate rather than proportionate poverty. Finally, estimations based on proportionate equation (equation 2.3) can be highly sensitive to the low initial poverty rate. So, purely on a statistical and mathematical basis, no proportionate poverty convergence can be observed when there is heterogeneity in the growth elasticity of poverty and high sensitivity in the low poverty rate.

One of the main differences between Ravallion (2012) and Cuaresma et al. (2017) is that the former focus on the growth elasticity of poverty given by Bourguignon (2003) and the latter focus on the semi-growth elasticity of poverty given by Klasen and Misselhorn (2008). Cuaresma et al. (2017) suggest to use the semi-elasticity of poverty proposed by Klasen and Misselhorn (2008) instead of the growth elasticity

[2]However they mention that this concept is good for at least two reasons. First equation 2.3 follows the two established effects in literature, i.e., income convergence and growth elasticity of poverty. Second, this concept is comparable to the income convergence literature in macroeconomics where the econometric equation also has a log-linear form.

of poverty. This concept is described as follows:

$$H_{it} = \delta_i^* + \eta_i^* ln\mu_{it} + \nu_{it}^* \tag{2.4}$$

Where H_{it} is the absolute poverty rate in the country i and time t, δ_i^* is the country-specific effects, and ν_i^* is the zero-mean disturbance term. The coefficient of η_i^* is assumed to be < 0, as higher income (consumption) is supposed to reduce poverty. This approach has the advantage over the previous approach (equation 2.2) because its sensitivity does not depend on the initial value. This approach is more appropriate from a welfare point of view. According to Cuaresma et al. (2017), equations (2.1) and (2.4) imply absolute poverty convergence, as I explained in the following equation (2.5).

$$\Delta H_{it} = \alpha_i^* + \beta_i^* H_{i,t-1} + \epsilon_{it}^* \tag{2.5}$$

Where, $\alpha^* = \alpha_i \eta_i - \beta_i \delta_i$, $\epsilon_{it}^* = \epsilon_{it}\eta_i + \nu_{it} - (1+\beta)_i \nu_{it-1}$ and $\beta_i^* = \beta_i$. A negative and statistically significant β_i indicates absolute poverty convergence, i.e., if initial poverty drops by one percentage point, the rate of poverty reduction increases by β_i^* percentage point. Adding some additional variables would give the estimates of conditional absolute poverty convergence. Likewise, in equation (3), the coefficients are equal $\beta_i^* = \beta_i$ in equation (5). The difference between equations (3) and (5) is the change in percentage points instead of proportionate percent change. By using the absolute convergence approach, Cuaresma et al. (2017) find convergence in poverty in the same data set as used by Ravallion (2012). Asadullah and Savoia (2018) provide evidence of absolute poverty convergence. They find that the poverty headcount and poverty gap tended to reduce faster in countries with high initial poverty. They argue that the substantial increase in poverty reduction is explained by the state capacity. The countries that have a better ability to manage their territories in 1990 experienced a fast poverty reduction, and they are more likely to have achieved the MDG's in 2015. A more effective state in terms of effective institutions and good governance could be vital to sustaining the development progress.

2.3 Empirical Approach

2.3.1 Basic Setup

The regression of interest is

$$g(\overline{y}_i) = \log \overline{y}_{i1} - \log \overline{y}_{i0} = \alpha + \beta \log \overline{y}_{i0} + u_i, \tag{2.6}$$

where $i = 1, ..., I$ indexes districts and 0 and 1 denote baseline and endline periods. $\overline{y}_{it}$ is a mean outcome of interest (consumption or a poverty measure) for district i in year t (=0, 1) calculated as a sample average from unit-level observations, which I index by j:

$$\overline{y}_{it} = \frac{1}{J_{it}} \sum\nolimits_{j=1}^{J_{it}} y_{ijt}.$$

There are J_{it} unit level observations in the sample for district i and year t.

Following Temple (1998), equation 2.6 may be re-written

$$\log \overline{y}_{i1} = \alpha + (1+\beta) \log \overline{y}_{i0} + u_i. \tag{2.7}$$

Given that $\overline{y}_{i0}$ is the mean of a (small) sample, it is clear that

$$\overline{y}_{i0} = \mu_{i0} + v_i,$$

where μ_{i0} denotes the true mean of y_{ij0} and v_i is the sampling error of $\overline{y}_{i0}$ relative to μ_{i0}.

I am interested in the true value of b in the regression.

$$\log \mu_{i1} = a + (1+b) \log \mu_{i0} + u_i.$$

Suppose that $0 > b > -1$, i.e. the process governing μ_{it} is not a random walk but a stationary process with some persistence. The OLS estimate of (1+β), (1+$\widehat{\beta}$), obtained from estimating (2.7) will be biased downward relative to $(1+b)$ whenever $V(v_i) > 0$, which implies that $\widehat{\beta}$ will be biased downward relative to b. To illustrate, suppose for example that $b = 0$, i.e. there is no convergence. The downward bias of $\widehat{\beta}$ may lead us to conclude that there is convergence.

2.3.2 Accounting for measurement error in convergence regressions

The bias of the OLS estimate of $(1+\beta)$ in equation (2.7) can be removed if I know the measurement error of $\log \overline{y}_{i0}$. When the Variance of v_i is known, a consistent estimator of $(1+\beta)$ is available through the so-called consistent adjusted least square (CALS) estimator, which has been introduced for more general cases by Kapteyn and Wansbeek (1984). The present case of a single contaminated regressor is dealt with in detail in Wansbeek and Meijer (2000). To illustrate, consider a simple linear regression model with dependent variable Y and a single, contaminated regressor, X say, where X is the sum of a 'true' value X^* and a stochastic, uncorrelated (measurement) error term, V. The procedure boils down to inflating the naive OLS estimate of the slope coefficient of that regression, β say, by the inverse of the so-called reliability coefficient of X, which is the ratio of the variance of X^* and the variance of X. To see how this adjustment yields a consistent estimate of the 'true' slope coefficient β^*, which is the slope coefficient in a counterfactual regression of Y on X^*, notice that β^* equals the ratio of the covariance of Y and X^* and the variance of X^*, while β equals the ratio of the covariance of Y and X and the variance of X. Now notice that the two covariances are the same because, by assumption, Y and V are uncorrelated. Further, by definition of the reliability coefficient, I have that the variance of X^* equals the variance of X times the reliability coefficient.

The crucial additional input for this estimation procedure is the reliability coefficient of the regressor $\log \overline{y}_{i0}$ in regression (2.7), which can also be written as

$$1 - \frac{\text{Measurement Error Variance}}{\text{Total Variance}}.$$

In other words, I need the measurement error variance, VN say, and total variance, V say, of $\log \overline{y}_{i0}$. The latter is simply the sample variance of $\log \overline{y}_{i0}$, where the variance is taken over the I observations, here districts, of $\overline{y}_{i0}$.

The measurement error variance of $\log \overline{y}_{i0}$ is less straightforward, on the other hand, because it is a non-linear function of the sample means $\overline{y}_{i0}$ and only the sampling variance of the latter can be estimated directly from household-level data. To assess $VN[\log \overline{y}_{i0}]$, in a first step I estimate $VN[\overline{y}_{i0}]$ by running the regression

$$y_{ij0} = d_i + w_{ij}, \tag{2.8}$$

where i indexes districts and j households. For mean consumption, y_{ij0} equals monthly per capita consumer expenditures (MPCE), for the poverty headcount ratio a binary household-level poverty indicator. Accounting for stratification in my survey data, I cluster standard errors at the first-stage-sampling-unit level and take the mean of the squared standard errors of the point estimates of $d_1, ..., d_I$ as estimate of $VN[\overline{y}_{i0}]$. At least in a scenario with homoskedastic error terms w_{ij} and a balanced number of households across districts, this is an unbiased estimator of $VN[\overline{y}_{i0}]$.

To approximate the sampling variance of $\log \overline{y}_{i0}$, I employ the delta method (see e.g. Appendix A.6 in Wansbeek and Meijer, 2000),

$$V[g(\overline{X})] \approx \left[g'(\mu)\right]^2 V(\overline{X}),$$

where X is a random variable with mean μ and g a continuously differentiable function, to obtain

$$VN[\log \overline{y}_{i0}] \approx \frac{VN[\overline{y}_{i0}]}{\overline{y}_0^2},$$

where $\overline{y}_0$ denotes average MPCE at baseline, that is in period zero. Notice that the latter expression resembles a squared coefficient of variation for $\overline{y}_{i0}$, where I focus exclusively on variation introduced by the sampling error, however.

2.4 Data

I use two data sets in this study: on the one hand, the much-explored National Sample Survey (NSS) in the case of India, and on the other hand, a much less explored Multiple Indicator Cluster Survey (MICS) in the case of Punjab-Pakistan. The NSS was conducted by the Indian government to collect socio-economic data and covered all the geographical regions of India. In this study, my focus is on 17 major states of India instead of the entirety of India. The reason for this is that the 17 major states cover almost 88 percent of India's overall population. These 17 major states are politically and economically more stable than other Indian states.

I use only two rounds of NSS (61^{st} in 2004-05 and 68^{th} in 2011-12) to compare the results with two rounds of MICS (2003-04 & 2010-11) in Pakistan. In total, the sample size is 249,321 in the 61^{st} round of NSS and 203,635 households in the 68^{th} round of NSS. To measure poverty, I use consumption-based rather than income-based indicators. The literature has established that consumption indicators are better than income indicators because current consumption is more stable and predictable when compared to income. There is also risk involved in measuring the income of households who are self-employed or are highly dependent on the agriculture sector. The income of these types of households can fluctuate highly and may severely bias the estimates of this study. Income is inferred as a measure of welfare opportunity, while consumption seems like a good measure of welfare achievement. The poverty line is the benchmark to separate the poor from the non-poor. The Planning commission of India publishes the state-wise poverty line by using the methodology of the Tendulkar commission. In the case of India, I measure poverty for the years 2004-05 and 2011-12 by using the poverty lines of respected years. I use separate poverty lines in each state, and I also use different poverty lines for rural and urban areas.

In the case of Pakistan-Punjab, I use the two rounds of the Multiple Indicator Cluster Survey (2003 & 2011). The Multiple Indicator Cluster Survey (MICS) provides the representative estimates of the household survey, covering more than 100 indicators disaggregated by the area of residence (urban and rural), 9 divisions, and 36 districts. In total, the sample size is 102,545 households in MICS 2011 and 30,932 households in MICS 2003 with an exceptional response rate of more than 95 percent. These surveys were planned, designed, and implemented by the Bureau of Statistics, Punjab-Pakistan with the help of the United Nations International Children's Fund (UNICEF) and the Pakistan Bureau of Statistics. One issue with the MICS 2011 is that this round has the section of quantities consumed and respective prices within the questionnaire, but the dataset does not include the prices of commodities. Thus, in order to calculate the values of the respective goods, this study uses price data from the Bureau of Statistics, Punjab-Pakistan. The Bureau of Statistics encompasses data on prices of more than 80 commodities from 9 regions of Punjab. The data has been collected at an interval of, on average, 1 to 4 days. This price data mitigates the problem of the misreporting of prices by the respondents. MICS 2003 has the quantity and price section, but for the sake of uniformity of the analysis, I apply the prices to the MICS 2003 from the Bureau of Statistics. To measure poverty for the years 2003 and 2011, I use the official poverty line of Rs. 1745 given by the Ministry of Planning, Development & Reforms, Pakistan, for the year 2011. This poverty line is used because the Pakistan Bureau of Statistics does not publish the consumer price index at the divisional or province levels. Thus, it is difficult to inflate or deflate the poverty line by using the provincial or regional level price index. To make poverty estimates more accurate and reliable, I develop a price index at the regional level from the survey data given by MICS and the price data given by the Bureau of Statistics, Punjab-Pakistan. I have regional price indices for both years, so I use the 2011 poverty line of 1745 rupee per month. Among different poverty measures available in the literature, I focus on the headcount ratio as defined as the share of the population living in the household which has a monthly per capita consumption expenditure (MPCE) below the poverty line.

2.5 Results

In this section, I present descriptive statistics and empirical results. Table 2.7 in the appendix provides the summary statistics for the initial and latest survey rounds. In the case of India, the mean consumption increases from Rs. 632 to Rs. 1422 between 2004-05 and 2011-12, respectively. In rural districts of India, the mean consumption increases from Rs. 558 to Rs. 1248 between 2004-05 and 2011-12, respectively. During this period, absolute poverty decreased from 40 percent to 27 percent in overall districts of India. The poverty reduction is also observed in rural and urban districts of India. In the case of Punjab-Pakistan, the mean consumption increases from Rs. 2342 to Rs. 3327 between 2003-04 and 2010-2011, respectively. Besides this, I observe poverty reduction during the same period in Punjab-Pakistan. The absolute poverty decreases from 47 percent to 28 percent. The same pattern of poverty reduction is observed in rural and urban districts of Punjab-Pakistan. Moreover, I find that poverty in districts increases as the distance of districts increases from Lahore district (capital of Punjab-Pakistan); besides this, districts mean consumption decreases with distance from Lahore district.

Now I discuss the advantages of backwardness by examining the mean consumption convergence in India and Punjab-Pakistan. Table 2.1 depicts the results of the mean consumption convergence by using different specifications. The estimation method is consistent adjusted least squares. In column 1, I do not find any evidence of mean convergence at the national level in India. Even I find little evidence of divergence in the districts of India, meaning that richer districts are growing faster than the poor districts. By adding the state fixed effect in column 2, I observe the convergence clubs in the mean consumption in India. The annual convergence coefficient is 0.015, which explains that a one percent increase in initial log mean consumption decreases the growth rate of mean consumption by 0.15 percent per year. Convergence clubs in mean consumption also observes in rural and urban districts of India in columns 5 and 8. The speed of mean convergence is faster in the rural district of India compared to urban districts. In columns 3, 6, and 9, I analyze the mean convergence across states of India. The results do not observe any evidence of mean convergence across the states.

Besides Indian districts, the evidence of mean consumption convergence observes in districts of Punjab-Pakistan. The coefficient of convergence is 0.091, which explains that a 1 percent increase in initial log consumption decreases the growth rate of consumption by 0.091 percent per year in overall districts of Punjab-Pakistan. The rural and urban districts are also converging with a speed of 0.092 percent and 0.123 percent, respectively. In all regression specifications, the measure of goodness of fit suggests that initial mean consumption explains a significant share of the variation in the growth of mean consumption. The regression results confirm that the districts with initially low mean consumption grow faster than the districts with an initially high level of mean consumption. I find that the speed of convergence in Punjab-Pakistan is higher than in Indian districts. In each regression specification, the reliability coefficient of initial mean consumption is reported in the table. The findings of Table 2.1 provide support in favor of the first stylized fact of economic development—initially poor districts are growing faster than the affluent districts. The evidence of mean consumption convergence also presented in figures A.1(a)—A.1(f), where the annualized growth rate of mean consumption plotted against initial mean consumption. All the figures are suggesting that the districts having initially lower mean consumption are growing faster than districts having high initial mean consumption. The "advantage of backwardness" is present at a subnational level in India and Pakistan. The results of mean consumption convergence are in line with the findings of Ravallion (2012).

This paragraph summarizes the discussion about the second stylized fact of economic development—advantages of growth. A famous argument in the literature of welfare economics is that economic growth in terms of increasing per capita income/consumption reduces poverty in developing countries. There is no consensus on the exact degree of poverty reduction through economic growth. The debate about the sensitivity of the distribution of poverty to per capita income/consumption has been going on for two decades (Bourguignon 2003; Klasen and Misselhorn 2008; World Bank 2000 and Ravallion and Chen 1999). Bourguignon (2003) applies the growth elasticity of poverty to examine how much poverty is decreased by increasing growth. Klasen and Misselhorn (2008) used semi-growth elasticity of poverty instead of growth elasticity of poverty. I analyze both concepts of elasticity. The estimation method is consistent adjusted least squares while analyzing the growth and semi-growth elasticity of poverty. The reliability coefficients of initial headcount and the growth rate of mean consumption are reported in both tables. In column 2 of Table 2.13 in the appendix, the point estimate of growth elasticity explains that a 1 percent increase in the growth rate of consumption decreases the end line poverty by 2.68 percent per year in overall districts of India. The point estimates of the semi-growth elasticity of poverty also show that the absolute change in mean consumption is helpful in reducing poverty in overall districts of India in Table 2.14. I observe the same pattern of results in rural and urban districts and states of India.

Table 2.1: Proportionate consumption convergence

	India									Pakistan-Punjab		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean consumption initial (log)	1.052***	0.893***	1.192**	0.983***	0.666***	1.119**	0.921***	0.744***	1.270**	0.357***	0.356***	0.136
	(0.028)	(0.038)	(0.072)	(0.036)	(0.060)	(0.086)	(0.050)	(0.071)	(0.162)	(0.068)	(0.086)	(0.090)
Constant	0.464***		-0.443	0.898***		0.033	1.291***		-1.094	5.347***	5.323***	7.175***
	(0.178)		(0.469)	(0.227)		(0.545)	(0.334)		(1.120)	(0.525)	(0.665)	(0.707)
Convergence coefficient	0.007*	-0.015***	0.027***	-0.002	-0.048***	0.017	-0.011	-0.037***	0.039	-0.091***	-0.092***	-0.123***
	(0.004)	(0.005)	(0.010)	(0.005)	(0.009)	(0.012)	(0.007)	(0.010)	(0.023)	(0.010)	(0.012)	(0.013)
Reliability	0.90	0.90	0.98	0.877	0.877	0.98	0.74	0.74	0.96	0.94	0.91	0.89
Observations	478	478	17	474	474	17	477	477	17	34	34	34
R-squared	0.770	0.826	0.949	0.643	0.755	0.921	0.496	0.557	0.811	0.554	0.467	0.077
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is logarithmic mean consumption in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial mean consumption refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial mean consumption (see section 2.3.2). In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Besides India, I observe that growth and semi-growth elasticity of poverty helps to reduce poverty in Punjab-Pakistan. The growth elasticity of poverty is 1.10 percent per year in Punjab-Pakistan. The coefficient is almost half compared to India. In rural and urban districts of Punjab-Pakistan, growth and semi-growth elasticity of poverty are also helpful in reducing poverty. Based on Table 2.13 and 2.14, I conclude that for the reduction of poverty, growth rate of mean consumption is the key factor in districts of India and Punjab-Pakistan. Ravallion (2012) finds that the annual growth elasticity of poverty is 1.085 in his study. At the subnational level in Pakistan, the annual coefficient of growth elasticity is very similar to the Ravallion (2012), while the coefficient in India is almost double than that of Ravallion (2012). In short, the findings of Tables 2.13 and 2.14 provide the support in favor of the second stylized fact. The growth rate of mean consumption is helpful in reducing poverty at the subnational level in India and Punjab-Pakistan.

Next, in the presence of the two stylized facts of economic development—there is consumption convergence and growth rate of consumption tends to reduce poverty—I expect to see the poverty convergence at the subnational level. The results of proportionate poverty convergence and absolute poverty convergence are presented in Tables 2.2 and 2.3. The estimation method is consistent adjusted least squares, while analyzing the growth and semi-growth elasticity of poverty. The reliability coefficient of initial headcount is reported in tables. I do not observe any evidence of proportionate poverty convergence in India at the national level. The convergence coefficient is statistically insignificant in column 1 of Table 2.2. In column 2, this study observes the convergence clubs in proportionate poverty at the state level in India. I also observe the proportionate poverty convergence at the rural and urban districts of India. Columns 3, 6, and 9 show the divergence in proportionate poverty across Indian states.

In Punjab-Pakistan, the coefficient of proportionate poverty convergence is reported in columns 10—12 of Table 2.2. In column 10, the convergence coefficient is 0.083, which explains that a one percent increase in initial poverty decreases the growth rate of poverty by 0.083 percent annually. In rural and urban districts, poverty convergence is also observed. The rural districts of Punjab-Pakistan are converging at the double speed compared to rural districts of India. In all regression specifications, the measure of goodness of fit suggests that initial poverty explains a significant share of the variation in poverty reduction.

The results of Table 2.2 are different from the Ravallion (2012). I find the evidence of proportionate poverty convergence at the subnational level, while Ravallion (2012) does not find it across countries. This study also observes poverty convergence clubs at the subnational level in India. However, Azevedo et al. (2016) cannot do it at the subnational level in Turkey. Ouyang et al. (2019) did not find any evidence of poverty convergence club across countries. The evidence of proportionate poverty convergence is also presented in figures A.2(a)—A.2(f), where the annualized growth rate of poverty reduction is plotted against initial poverty rate. All the figures are suggesting that the districts having initially lower mean consumption are growing faster than districts having high initial mean consumption.

This study also provides evidence of poverty convergence by following the approach of Cuaresma et al. (2017). The evidence of absolute poverty convergence is presented in Table 2.3. I find strong evidence of absolute poverty convergence in overall districts of India. Poor districts have a higher pace of poverty reduction than affluent districts. When analysis is disaggregated at rural and urban districts, absolute poverty convergence is observed in both areas. However, across the states in India, this study does not find any evidence of absolute convergence in columns 3, 6, and 9. The convergence coefficient is statistically insignificant. The absolute poverty convergence is also observed in Punjab-Pakistan. The coefficient of convergence is 0.101 in column 10 of Table 2.3, suggesting that a one percentage point increase in initial poverty decreases the annual change in poverty by 0.101 percentage points. This study observes a very similar rate of absolute poverty convergence in the overall and rural districts of India and Punjab-Pakistan. By comparing the results of absolute poverty convergence with Cuaresma et al. (2017), this study documents a higher coefficient of poverty convergence 0.070 and 0.098 in India and Punjab-Pakistan, respectively. In Cuaresma et al. (2017) findings, the absolute poverty convergence is 0.015 across countries. Likewise, in proportionate poverty convergence, the coefficient of absolute poverty convergence is also higher at subnational analysis compared to cross-country analysis.

As this study finds evidence of consumption and poverty convergence, I turn to analyze whether the speed of consumption convergence and poverty convergence is equal—according to equation (2.3) and (2.5) in section 2.2—in India and Punjab-Pakistan. In Table 2.4, I report the convergence coefficients of mean consumption and poverty.

In the overall districts of India, I find that the coefficient of proportionate poverty convergence is triple the coefficient of mean convergence. However, in rural districts of India, I find the same coefficient of mean convergence (0.048) and proportionate poverty convergence (0.047). In India, the speed of poverty convergence is faster than the mean consumption convergence in overall districts of India. It might be the reason that initially poor districts are worse in exploiting the growth for poverty reduction, but initially poor districts grow faster conditional on initial mean consumption. For Punjab-Pakistan, a very similar speed of mean convergence and proportionate poverty convergence is observed in this study. Column 4 of Table 2.4 shows that the coefficient of consumption convergence is 0.091, and the coefficient of proportionate poverty convergence is 0.083 in Punjab-Pakistan. The absolute values of both the coefficients are very close. Likewise, the proportionate poverty convergence, a very close speed of mean convergence, and absolute poverty convergence are also observed in Punjab-Pakistan. Based on these coefficients, I can say that the speed of mean convergence and poverty convergence is the same at the subnational level in Punjab-Pakistan in accordance with the equation 2.3 in section 2.2. To the best of my knowledge, this is the first study that provides empirical evidence that the speed of mean consumption convergence and poverty convergence is equal. Ravallion (2012) is unable to provide the empirical evidence of equation 2.3. The result suggests that a similar speed of proportionate poverty convergence and mean convergence may only be observed at the subnational level. At a subnational level, there are fewer chances of heterogeneity and macroeconomic volatility in the data. It might also be possible for a similar speed of mean consumption and poverty convergence that people are close to the poverty line. Hence, as their income increases, they are out of poverty.

The results of poverty convergence are different from Das et al. (2010). They find the poverty convergence across the fourteen major states of India, while this study finds the divergence in proportionate poverty across the states. Moreover, this study does not find any evidence of overall convergence or divergence at the national level. However, within states, I find evidence of proportionate poverty convergence. Besides poverty convergence, Das et al. (2010) find the divergence in mean consumption across the rural states and convergence across India's urban states. However, this study does not find any evidence of convergence and divergence across the rural and urban states of India. I find the mean consumption convergence within states in rural and urban sectors. The main difference between the two studies is the methodology of convergence. Das et al. (2010) use the panel unit root approach to analyze the convergence, while this study uses the consistent adjusted least square approach to analyze the convergence. Besides methodology, Das et al. (2010) focus on the state level analysis, while this study's focus is at the district level.

2.5.1 Standard convergence approach

To highlight the issue of measurement error in the convergence literature, I examine the convergence in mean consumption and poverty by using the ordinary least squares estimates. Table 2.8—2.10 shows the results of ordinary least squares estimates. In Table 2.8, the regression coefficient exhibits mean consumption convergence in all cases of India and Punjab-Pakistan. The pattern of results is the same as I observed in Table 2.1. The speed of mean consumption convergence is twice in Punjab-Pakistan than India. The estimated results of Table 2.9 show the evidence of proportionate poverty convergence clubs at the state level in India. I find the proportionate poverty convergence in Punjab-Pakistan. Moreover, the evidence of absolute poverty convergence also presents in India and Punjab-Pakistan in Table 2.8.

If I compare the results of consistent adjusted least squares and ordinary least squares regressions, I can see a clear-cut difference between the magnitude of coefficients. In some cases, statistical significance also changed. In the case of mean convergence, I observe convergence at a 10 percent level of significance in column 1 of Table 2.8 by using ordinary least square estimates. In contrast, in column 1 of Table 2.1, the convergence disappears by using consistent adjusted least squares regression. Moreover, in columns 4 and 7 of Table 2.8, there is a sign of convergence in rural and urban districts, while in columns 4 and 7 of Table 2.1, the coefficient is not different from zero. In remaining cases, the convergence coefficients are more modest by using the consistent adjusted least squares in all specifications than ordinary least square estimates in India. In the case of Punjab-Pakistan, the significance does not change in any case; however, the convergence coefficient reduced in consistent adjusted least squares regressions. The difference in the magnitude of convergence coefficient between two regression approaches is larger in India compared to Punjab-Pakistan.

Table 2.2: Proportionate Poverty Convergence

	India									Pakistan-Punjab		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HCR initial (log)	1.012***	0.684***	1.543**	0.813***	0.673***	1.465**	0.976***	0.810***	1.746**	0.419***	0.393***	0.260***
	(0.053)	(0.058)	(0.146)	(0.059)	(0.064)	(0.156)	(0.083)	(0.095)	(0.374)	(0.066)	(0.067)	(0.063)
Constant	-0.664***		-0.027	-0.681***		-0.043	-0.659***		0.355	-0.971***	-0.940***	-1.304***
	(0.076)		(0.191)	(0.065)		(0.147)	(0.103)		(0.491)	(0.075)	(0.080)	(0.086)
Convergence coefficient	0.002	-0.045***	0.078***	-0.027***	-0.047***	0.066***	-0.003	-0.027**	0.107**	-0.083***	-0.087***	-0.106***
	(0.008)	(0.008)	(0.021)	(0.008)	(0.009)	(0.022)	(0.012)	(0.014)	(0.053)	(0.009)	(0.010)	(0.009)
Reliability	0.92	0.92	0.99	0.85	0.85	0.97	0.71	0.71	0.92	0.94	0.92	0.90
Observations	476	476	17	474	474	17	475	475	17	34	34	34
R-squared	0.457	0.670	0.883	0.322	0.459	0.859	0.292	0.424	0.612	0.477	0.443	0.240
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is logarithmic headcount ratio in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial headcount ratio (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial headcount (see section 2.3.2). In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.3: Absolute Poverty Convergence

	India									Pakistan-Punjab		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HCR initial	0.735***	0.507***	0.904**	0.612***	0.509***	0.874**	0.593***	0.448***	0.948**	0.316***	0.324***	0.143***
	(0.030)	(0.038)	(0.091)	(0.038)	(0.045)	(0.113)	(0.053)	(0.062)	(0.191)	(0.050)	(0.059)	(0.049)
Constant	-0.0289**		-0.094*	0.0273		-0.089	0.0184		-0.099	0.127***	0.137***	0.158***
	(0.014)		(0.036)	(0.018)		(0.049)	(0.020)		(0.055)	(0.023)	(0.025)	(0.025)
Convergence coefficient	-0.038***	-0.070***	-0.014	-0.055***	-0.070***	-0.018	-0.058***	-0.079***	-0.007	-0.098***	-0.097***	-0.122***
	(0.004)	(0.005)	(0.013)	(0.005)	(0.006)	(0.016)	(0.008)	(0.009)	(0.027)	(0.007)	(0.008)	(0.007)
Reliability	0.92	0.92	0.99	0.85	0.85	0.97	0.71	0.71	0.92	0.94	0.92	0.90
Observations	478	478	17	474	474	17	477	477	17	34	34	34
R-squared	0.577	0.727	0.870	0.399	0.498	0.803	0.271	0.398	0.641	0.493	0.451	0.193
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is headcount ratio in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial headcount refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial headcount (see section 2.3.2). In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.4: Comparison of Convergence Coefficients

	India			Pakistan-Punjab		
Convergence coefficient	Overall	Rural	Urban	Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)
Mean consumption convergence	-0.015***	-0.048***	-0.037***	-0.091***	-0.092***	-0.123***
Proportionate poverty convergence	-0.045***	-0.047***	-0.027**	-0.083***	-0.087***	-0.106***
Absolute poverty convergence	-0.070***	-0.070***	-0.079***	-0.098***	-0.097***	-0.122***

Notes: This table is constructed based on the results of Tables 2.1, 2.2, and 2.3. I take the convergence coefficients of column 2 from each table in the case of India. In contrast, take the convergence coefficients of columns 10, 11 and 12 in Pakistan's case. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

2.5.2 Two distinct poverty effects

In the present study, I observe the proportionate poverty convergence in India and Punjab-Pakistan. In particular, I analyze whether poverty convergence in the two countries is due to the absence of two distinct poverty effects. The discussion regarding the direct effect of poverty is summarized in Table 2.5—does initial poverty predict a slower subsequent growth rate? The estimation procedure is consistent adjusted least-squares while estimating the results of Table 2.5. The estimates of Table 2.5 suggest that, for a given initial mean consumption, the initial rate of poverty does not impede subsequent growth in consumption in India and Punjab-Pakistan. Moreover, the coefficient of initial poverty is positive and statistically significant, meaning that districts which start out at a higher level of poverty have a faster growth in mean consumption in the two countries. The direct association between initial poverty and subsequent growth in mean consumption is likely to be related to strong policy orientation which transfers public resources towards the poor regions during this period. The reliability coefficients of initial mean consumption and initial headcount are reported in both tables. Due to the violation of full rank condition, the regression results are not identified in columns 5,7-9 and 12.[3]

The findings of Table 2.5 are different from Ravallion (2012) in two respects. Firstly, Ravallion finds a negative and statistically significant effect of initial poverty on growth and points out that the initial poverty is the main hurdle to counterbalance the mean convergence effect. This study documents that high initial poverty appears to grow faster and lead to poverty convergence at the subnational level in India and Pakistan. The structure of growth in these two South Asian countries is different from that of the rest of the developing world; in developing countries, the high initial poverty is the leading cause in the absence of poverty convergence.

Secondly, the growth elasticity of poverty depends on initial poverty. The discus-

[3]The CALS regression estimator is

$$b = (X'X - S)^{-1} X'Y = A^{-1} X'Y \tag{2.9}$$

where $A = (X'X - S)$. Lockwood and McCaffrey (2020, p. 119) explain that the estimator b in (2.9) "requires A to invertible. In addition the estimator b is conventionally taken to be well defined only when the estimated variance-covariance matrix of $(Y_i,\ X^*_{i1},\ldots,X^*_{ip})$ is positive semi-definite. Either of these conditions may fail to hold for a given set of observations and working reliabilities, in which case we say that b "does not exist"." For further details see Fuller (1987) and Fuller and Hidiroglou (1978).

sion regarding the indirect effect of poverty is summarized in Table 2.6—is poverty a handicap for the poverty-reducing effect of growth? The results in Table 2.6 indicate that the growth elasticity of poverty contributes significantly to poverty reduction across overall districts of India. The interaction term of initial poverty and growth rate of mean consumption appears significant in overall districts of India. Column 2 of Table 2.6 suggests that poverty is a handicap for the poverty-reducing effect of growth in overall districts of India. However, the coefficient of interaction terms is negative across the states in column 3.

The findings of Table 2.6 stand in line with Ravallion (2012). He finds that the initial poverty is a handicap for the poverty-reducing effect of growth across developing countries. Besides the overall districts of India, the regressions do not identify due to the low reliability of the regressors in any case. Due to the violation of full rank condition, regressions are not identified in India's rural and urban sectors and all cases of Punjab-Pakistan.[4] However, the regressions are identified when I use the reliability of one or two variables in regression instead of the reliability of three regressors. I also report the ordinary least square estimates in Table 2.5 and 2.6. These results are available in Table 2.11 and 2.12 in appendix. The findings of Table 2.11 and 2.12 support the results of consistent adjusted least squares estimation.

In short, the overall districts of India observe poverty convergence, while there is evidence to suggest indirect adverse effects of poverty. The result of India's overall districts suggests that a country can observe poverty convergence even with the presence of an indirect poverty effect. Punjab-Pakistan observes poverty convergence in the absence of adverse direct poverty effects, while the results are not identified for indirect poverty effects.

In the next step I explain the possible reasons why Indian districts observe poverty convergence. First, it could be the fruits of economic reforms that started in 1990. Just after the economic reforms, the disparities increased between states (Bajpai and Sachs 1996; Rao et al. 1999). However, Ahluwalia (2000) argues that implementation of reforms has led to substantial growth and reduced the difference between rich and poor states. So, it might be possible that the fruits of economic reform showed up after only one decade. Second, it could also be the effect of the

[4] See footnote 3.

eleventh five-year plan (2007-11). The central objective of this plan is to make growth more inclusive and faster. So, the fruits of inclusive growth should be shared by those people who have been ignored during the high rate of economic growth. The two above-mentioned reasons are both potential factors for poverty convergence in India. Besides India, this study argues that fiscal decentralization is helpful for the process of poverty convergence at the subnational level in Punjab-Pakistan. First, the literature suggests that the condition of poverty and the distribution of income is expected to improve at the national level if regions exhibit income convergence during decentralization. The literature identifies that decentralization is helpful not only for regional development (Faguet 2014), but also for employment generation (Martinez-Vazquez and Yao 2009), and the welfare of the poor (Martinez-Vazquez 2001). On the one hand, at the subnational level in Pakistan, Punjab experienced decentralization from 2001 to 2009. On the other hand, the present study finds evidence of consumption convergence as well as poverty convergence. Second, the share of health and education expenditures increased in total government expenditure during fiscal decentralization (Arze del Granado et al. 2005 & Martinez-Vazquez 2001). This study finds that the condition of health improved in districts, as measured by rural health clinics, basic health units as well as maternity and child health clinics. This study also finds that the condition of education improved in different districts of Punjab, as measured by different indicators of education such as the total enrollment of primary and high schools as well as girls' enrollment in primary and high schools. Third, Shahzad and Yasmin (2016) find that the combined effect of fiscal decentralization and institutions has a negative impact on poverty in the case of Pakistan. Fiscal decentralization helps to reduce poverty with the help of good quality institutions. During the time frame of the study, Punjab experienced decentralization and institutional quality also improved in Punjab-Pakistan. On the basis of the above three reasons, I may argue that decentralization also plays its role in poverty convergence.

The results of this study support the argument that growth is uneven in developing countries. Developing countries behave differently in response to policies of poverty reduction based on the initial conditions and potential resources of that country. The effect of the initial condition on poverty may be positive in one country but harmful for another country. In Ravallion (2012), initial poverty slows down the growth process in the developing world, but in a single country, the case would be different. When I analyze the effect of high initial poverty on growth, I find a different story when compared to cross-country study. The high initial poverty contributes positively to the growth process of both India and Pakistan. I observe that within-country Punjab-Pakistan experienced balanced growth during the study period. However, in India, the initial poverty helps to improve the subsequent growth, but I observe the convergence clubs in mean consumption and poverty.

2.5.3 Will poverty be eradicated by 2030? A policy discussion

Fast economic growth in countries such as China and India help to lift millions of people out of poverty. However, I cannot generalize this to other regions of the world. Poverty is still widespread worldwide, with higher poverty rates in South Asia and Sub-Saharan Africa. Eighty percent of the extreme poor live in South Asia and Sub-Saharan Africa. UNDP announced sustainable development goals (SDGs) for 2030 to eradicate poverty from the world. How reliable are the results of this study to predict whether the SDGs will be reached by 2030 in India and Pakistan? Let us begin with the poverty rate of the year 2010-11 and the magnitude of absolute poverty convergence. These values imply an extreme poverty incidence of 19.67 percent in 2030 in Punjab-Pakistan. This poverty rate is far off the SDGs of poverty eradication. If I apply this exercise on the district level, I find an even higher rate of poverty incidence for the districts that have higher poverty incidence. When applying the same exercise to India, I find that there will be 8 percent poverty in India in 2030. This study suggests that, even though growth seems to be suitable in reducing poverty, it is not sufficient to eliminate poverty and meet the SDGs for 2030.

Table 2.5: Does High Poverty Slow Down Growth?

	India									Pakistan-Punjab		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean consumption initial (log)	1.567***	1.406***	1.801**	2.200***		1.417				1.004**	1.741***	
	(0.065)	(0.081)	(0.181)	(0.084)		(0.856)				(0.369)	(0.614)	
HCR initial (log)	0.196***	0.189***	0.278**	0.595***		0.261				0.366*	0.757**	
	(0.022)	(0.024)	(0.079)	(0.038)		(0.740)				(0.202)	(0.329)	
Constant	-2.599***		-4.085**	-6.180***		-1.622				0.674	-4.683	
	(0.391)		(1.095)	(0.493)		(4.773)				(2.671)	(4.441)	
Reliability (Mean consumption initial (log))	0.900	0.900	0.98	0.877	0.877	0.98	0.740	0.740	0.96	0.940	0.910	0.890
Reliability (HCR initial (log))	0.920	0.920	0.99	0.850	0.850	0.97	0.710	0.710	0.92	0.940	0.920	0.900
Observations	478	478	17	474		17				34	34	
R-squared	0.824	0.863	0.976	0.853		0.923				0.665	0.736	
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is logarithmic mean consumption in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial mean consumption refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficients of initial mean consumption and initial headcount ratio (see section 2.3.2). In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. In columns 5, 7, 8,9, and 12, the regression is not identified due to the low reliability of the initial mean consumption and initial headcount ratio. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.6: Is Poverty a Handicap for the Poverty-reducing Effect of Growth?

	India									Pakistan-Punjab		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HCR initial (log)	0.241***	0.192**	1.673**									
	(0.081)	(0.095)	(0.105)									
ΔMean consumption (log)	-40.24***	-38.83***	-24.473**									
	(1.626)	(2.581)	(1.231)									
HCR*ΔMean consumption (log)	34.87***	36.50***	-10.206**									
	(2.867)	(4.104)	(3.162)									
Constant	1.386***		3.365**									
	(0.147)		(0.184)									
Reliability of HCR initial (log)	0.920	0.920	0.990	0.850	0.850	0.970	0.710	0.710	0.920	0.940	0.92	0.90
Reliability of ΔMean consumption (log)	0.916	0.916	0.985	0.895	0.895	0.985	0.771	0.771	0.955	0.943	0.915	0.878
Reliability of HCR*ΔMean consumption (log)	0.918	0.918	0.988	0.873	0.873	0.978	0.741	0.741	0.938	0.941	0.918	0.889
Observations	476	476	17									
R-squared	0.823	0.844	0.998									
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is logarithmic headcount ratio in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial headcount ratio (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficients of initial headcount ratio, growth rate of mean consumption and interaction term of headcount ration with growth rate of mean consumption (see section 2.3.2). In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. In columns 3—12, the regressions are not identified due to the low reliability of the explanatory variables. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

2.6 Conclusion

The objective of many development policies is to achieve sustained economic growth and reduce poverty. This study revisits two distinct effects of poverty at the subnational level in India and Punjab-Pakistan. First, does high poverty slow down growth, a direct poverty effect? Second, is high poverty a handicap for the poverty-reducing effect of growth, an indirect poverty effect? In the case of India, I do not find any evidence of convergence in mean consumption and poverty, but I do observe convergence clubs in mean consumption and poverty. The speed of convergence in mean consumption and poverty is slower in India than in Punjab-Pakistan. In the case of Punjab-Pakistan, I find evidence of mean consumption convergence and poverty convergence. I also observe poverty and consumption convergence of the same magnitude.

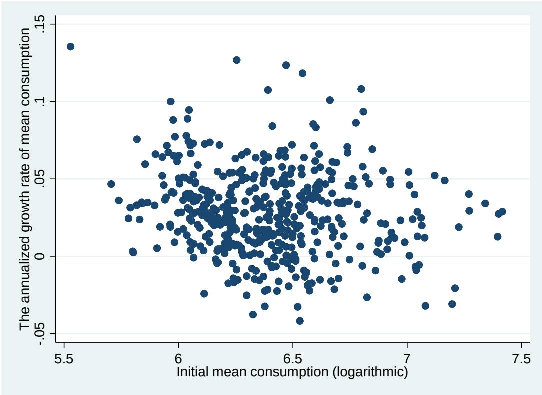
To the best of my knowledge, this is the first study which finds a very similar speed of consumption convergence and proportionate poverty convergence at the subnational level in Punjab-Pakistan and rural districts of India. In both countries, high initial poverty is helpful in increasing the subsequent growth rate. The presence of an indirect poverty effect can be observed at the state level in India. This study discusses the potential reasons why there is poverty convergence in these two countries. In India, economic reforms and the eleventh five-year plan are the potential reasons, while in Punjab-Pakistan, fiscal decentralization is the potential reason for poverty convergences.

This study supports the argument that growth is uneven in developing countries. Every developing country behaves differently regarding poverty reduction and convergence, based on the different initial conditions and potential resources of that country. The effect of initial conditions on growth and poverty may be different within less developed countries. I suspect that, due to the unevenness of growth within developing countries, the previous literature did not find evidence in favor of proportionate poverty convergence across countries. Based on absolute poverty convergence, this study finds an extreme poverty incidence of 19.67 percent in 2030 in Punjab-Pakistan and 8 percent in India, which is far off the SDGs of poverty elimination. This study suggests that, even though growth seems to be suitable for reducing poverty, it is not sufficient to eliminate poverty and meet the SDGs for 2030. Focusing on inclusive growth and designing policies that are helpful for lagging districts, may be crucial for all developing countries to eliminate poverty.

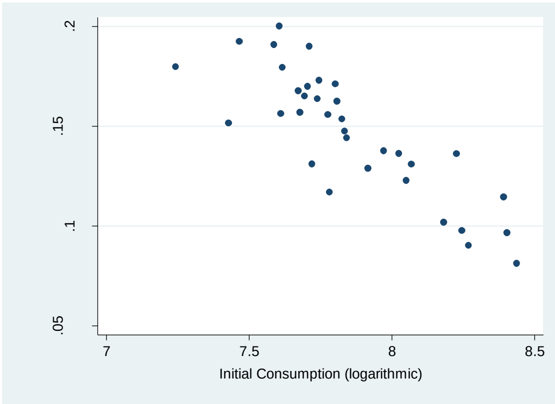
Appendix

Figure A.1: Convergence in consumption

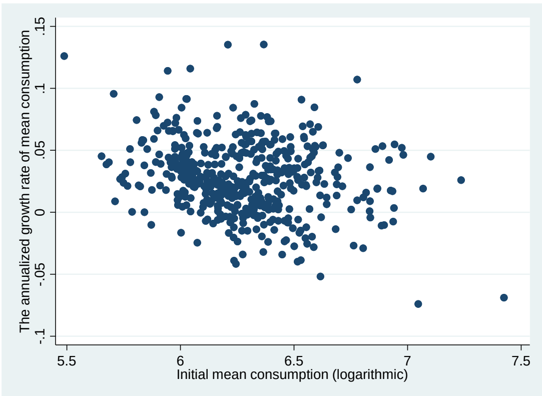
A.1(a)Overall mean consumption convergence in India



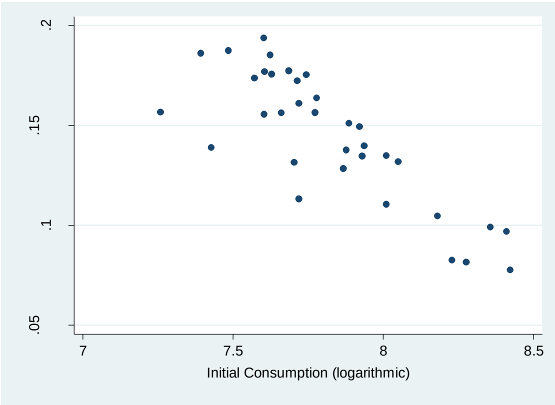
A.1(b) Overall mean consumption convergence in Punjab-Pakistan



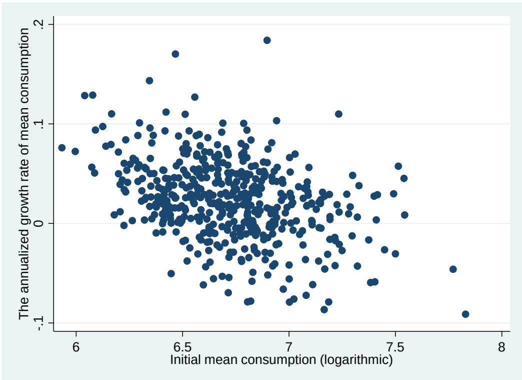
A.1(c) Rural mean consumption convergence in India



A.1(d) Rural mean consumption convergence in Punjab-Pakistan



A.1(e) Urban mean consumption convergence in India



A.1(f) Urban mean consumption convergence in Punjab-Pakistan

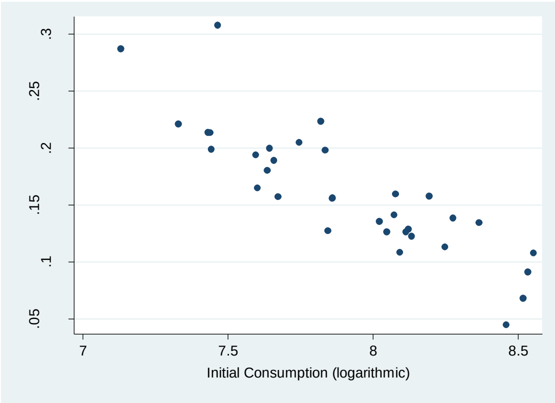
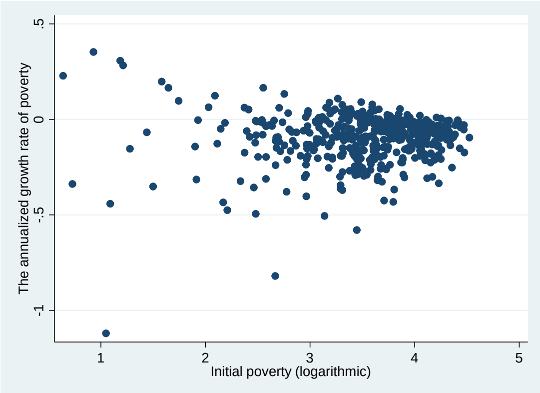
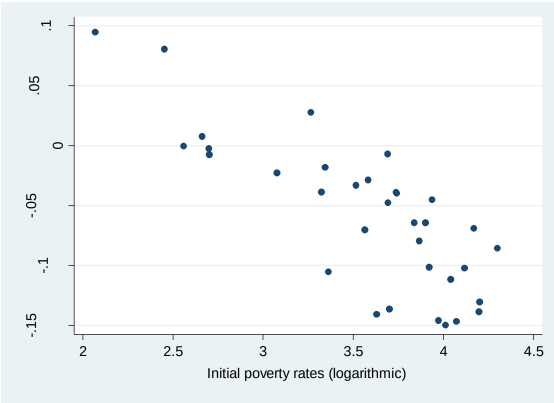


Figure A.2: Proportionate Poverty Convergence

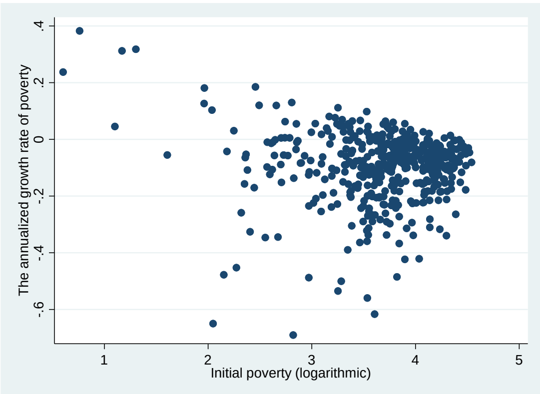
A.2(a) Overall proportionate poverty convergence in India



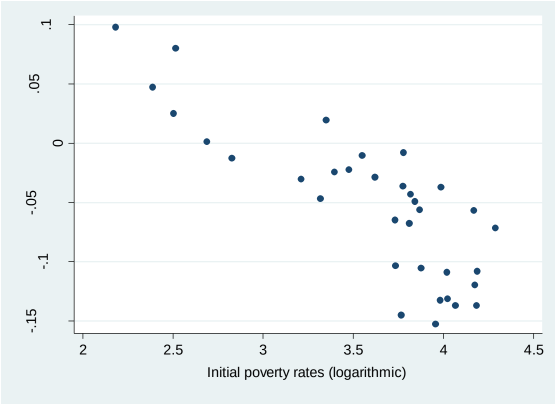
A.2(b) Overall proportionate poverty convergence in Punjab-Pakistan



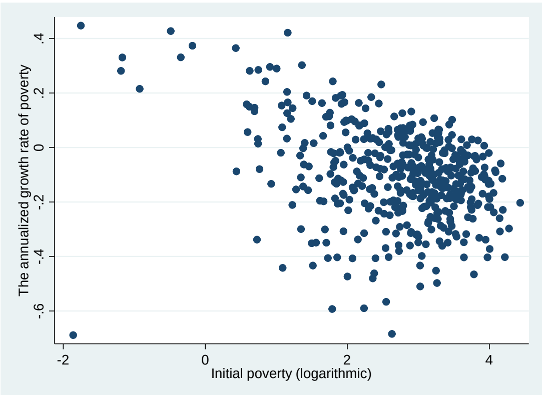
A.2(c) Rural proportionate poverty convergence in India



A.2(d) Rural proportionate poverty convergence in Punjab-Pakistan



A.2(e)Urban proportionate poverty convergence in India



A.2(f) Urban proportionate poverty convergence in Punjab-Pakistan

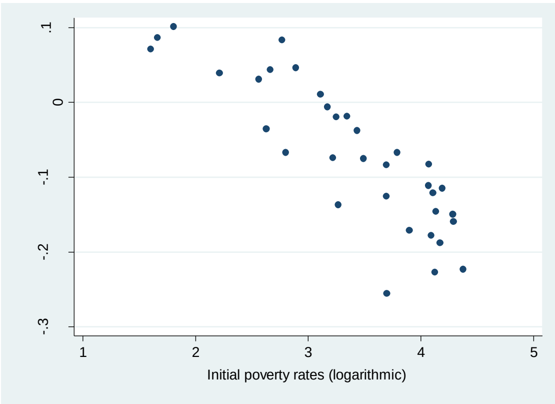
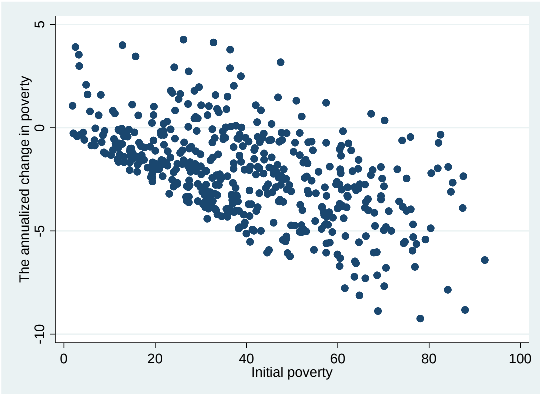
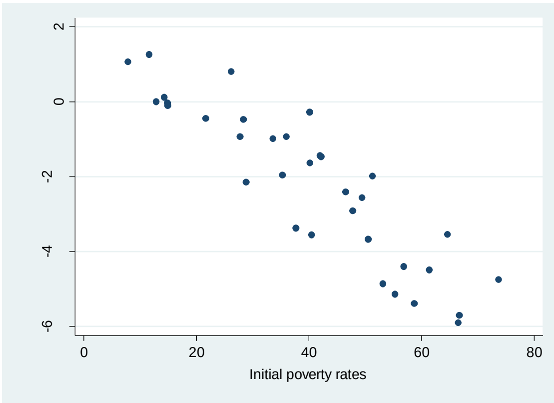


Figure A.3: Absolute Poverty Convergence

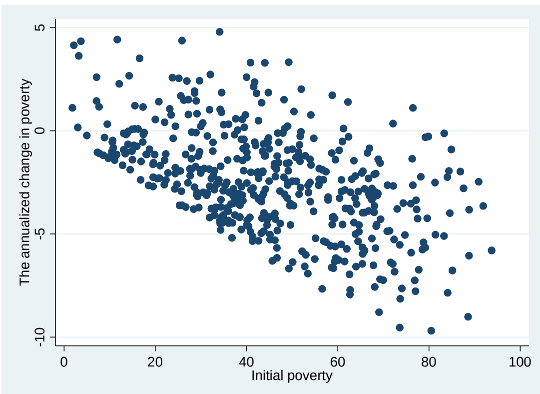
A.3(a) Overall absolute poverty convergence in India



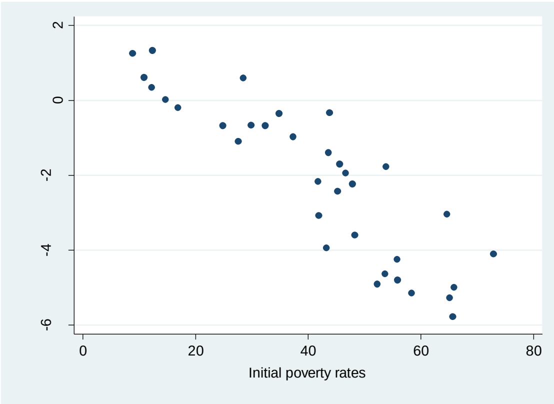
A.3(b) Overall absolute poverty convergence in Punjab-Pakistan



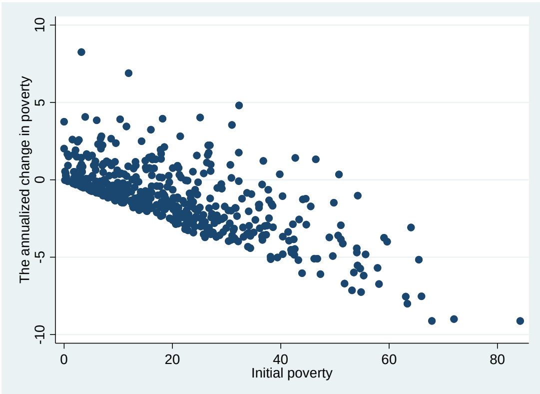
A.3(c) Rural absolute poverty convergence in India



A.3(d) Rural absolute poverty convergence in Punjab-Pakistan



A.3(e) Urban absolute poverty convergence in India



A.3(f) Urban absolute poverty convergence in Punjab-Pakistan

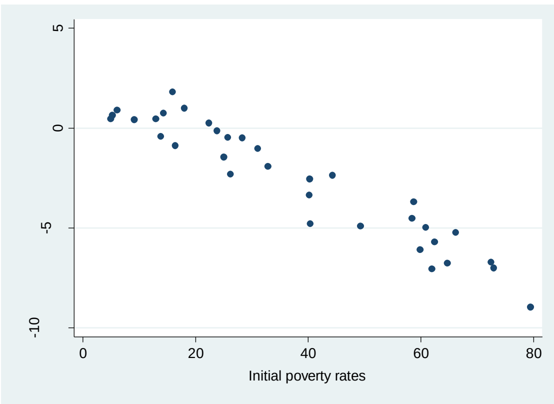


Table 2.7: Descriptive Statistics

	Overall				Rural				Urban			
	Districts	Observations	Mean	SD	Districts	Observations	Mean	SD	Districts	Observations	Mean	SD
India												
Mean consumption 2004-05	478	199,588	632.50	221.27	474	126,986	558.63	170.14	477	72,602	876.12	285.24
Mean consumption 2011-12	478	161,084	1422.42	560.99	474	95,269	1248.60	431.26	477	65,815	1893.62	691.07
HCR 2004-05	478	199,588	0.40	0.22	474	126,986	0.44	0.20	476	72,602	0.36	0.18
HCR 2011-12	476	161,084	0.27	0.21	474	95,269	0.30	0.18	476	65,815	0.23	0.17
Pakistan-Punjab												
Mean consumption 2003-04	34	30,758	2342.86	755.69	34	18,560	2273.92	727.02	34	12,198	2524.10	966.07
Mean consumption 2010-11	34	102,545	3327.49	460.14	34	60,498	3190.03	447.94	34	42,047	3820.30	694.51
HCR 2003-04	34	30,758	0.47	0.20	34	18,560	0.49	0.20	34	12,198	0.44	0.24
HCR 2010-11	34	102,545	0.28	0.09	34	60,498	0.29	0.09	34	42,047	0.22	0.07

Note: Author's calculation based on NSS and MICS data.

Table 2.8: Proportionate Consumption Convergence: Ordinary Least Squares Estimation

	India									Pakistan-Punjab		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean consumption initial (log)	-0.008*	-0.040***	0.025**	-0.020***	-0.076***	0.014	-0.046***	-0.079***	0.031	-0.095***	-0.097***	-0.126***
	(0.004)	(0.006)	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.007)	(0.019)	(0.009)	(0.012)	(0.012)
Constant	0.162***		-0.050	0.237***		0.025	0.415***		-0.106	0.787***	0.796***	1.042***
	(0.026)		(0.045)	(0.035)		(0.047)	(0.040)		(0.129)	(0.074)	(0.089)	(0.094)
Observations	478	478	17	474	474	17	477	477	17	34	34	34
R-squared	0.007	0.276	0.255	0.032	0.393	0.067	0.112	0.282	0.102	0.810	0.763	0.793
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is the growth rate of mean consumption in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial mean consumption (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is the β in first row. The estimation method is ordinary least squares. In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.9: Proportionate Poverty Convergence: Ordinary Least Squares Estimation

	India									Pakistan-Punjab		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HCR initial (log)	-0.010	-0.058***	0.075**	-0.044***	-0.065***	0.060**	-0.044***	-0.069***	0.087*	-0.087***	-0.091***	-0.109***
	(0.017)	(0.016)	(0.009)	(0.011)	(0.011)	(0.020)	(0.011)	(0.012)	(0.035)	(0.009)	(0.009)	(0.008)
Constant	-0.108***		-0.006	-0.114***		-0.012	-0.141***		0.025	-0.142***	-0.138***	-0.190***
	(0.017)		(0.016)	(0.009)		(0.020)	(0.0120)		(0.043)	(0.011)	(0.011)	(0.012)
Observations	476	476	17	474	474	17	475	475	17	34	34	34
R-squared	0.004	0.406	0.453	0.070	0.267	0.305	0.049	0.246	0.155	0.659	0.683	0.746
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is the growth rate of headcount ratio in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial headcount ratio (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is the β in first row. The estimation method is ordinary least squares. In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.10: Absolute Poverty Convergence: Ordinary Least Squares Estimation

	India									Pakistan-Punjab		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HCR initial	-0.046***	-0.082***	-0.015	-0.069***	-0.086***	-0.022	-0.083***	-0.103***	-0.018	-0.100***	-0.100***	-0.124***
	(0.004)	(0.005)	(0.007)	(0.005)	(0.005)	(0.017)	(0.006)	(0.006)	(0.019)	(0.007)	(0.008)	(0.006)
Constant	-0.0008		-0.013**	0.010***		-0.011	0.012***		-0.011	0.019***	0.021***	0.024***
	(0.002)		(0.004)	(0.002)		(0.007)	(0.002)		(0.006)	(0.003)	(0.003)	(0.003)
Observations	478	478	17	474	474	17	477	477	17	34	34	34
R-squared	0.206	0.504	0.079	0.303	0.431	0.102	0.311	0.453	0.030	0.829	0.798	0.906
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is the annualized change in headcount ratio in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial headcount ratio refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is the β in first row. The estimation method is ordinary least squares. In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.11: Does High Poverty Slow Down Growth? Ordinary Least Squares Estimation

	India									Punjab-Pakistan		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean consumption initial (log)	0.004	-0.033***	0.080*	0.012	-0.071***	-0.010	-0.035**	-0.083***	0.096*	-0.082***	-0.084***	-0.148***
	(0.007)	(0.007)	(0.030)	(0.010)	(0.012)	(0.057)	(0.014)	(0.013)	(0.035)	(0.0246)	(0.028)	(0.024)
HCR initial (log)	0.005***	0.003*	0.025	0.018***	0.002	-0.021	0.006	-0.002	0.049	0.008	0.007	-0.013
	(0.002)	(0.002)	(0.012)	(0.004)	(0.003)	(0.049)	(0.007)	(0.007)	(0.025)	(0.011)	(0.012)	(0.011)
Constant	0.094**		-0.375	0.056		0.156	0.351***		-0.492*	0.695***	0.707***	1.204***
	(0.043)		(0.181)	(0.058)		(0.319)	(0.085)		(0.215)	(0.173)	(0.203)	(0.180)
Observations	478	478	17	474	474	17	476	476	17	34	34	34
R-squared	0.016	0.280	0.413	0.083	0.393	0.083	0.110	0.277	0.166	0.813	0.766	0.799
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is the growth rate of mean consumption in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial mean consumption (logarithmic) and headcount ration (logarithmic) refer to 2004-05 for India and 2003-04 for Punjab-Pakistan. The estimation method is ordinary least squares. In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.12: Is Poverty a Handicap for the Poverty-reducing Effect of Growth? Ordinary Least Squares Estimation

	India									Punjab-Pakistan		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HCR initial (log)	-0.073***	-0.079***	0.055	-0.074***	-0.074***	0.181	-0.052***	-0.051***	0.328	-0.066***	-0.064***	-0.082***
	(0.017)	(0.016)	(0.039)	(0.013)	(0.012)	(0.138)	(0.015)	(0.015)	(0.278)	(0.017)	(0.022)	(0.013)
ΔMean consumption (log)	-4.546***	-3.513***	-3.773**	-3.245***	-3.401***	-0.135	-2.594***	-2.243***	0.248	-1.545***	-1.101*	-0.927*
	(0.318)	(0.317)	(0.508)	(0.216)	(0.261)	(1.469)	(0.256)	(0.253)	(2.688)	(0.521)	(0.569)	(0.530)
HCR*ΔMean consumption (log)	3.247***	2.495***	-0.249	1.991***	2.075***	-3.189	1.601***	1.097***	-8.558	1.479**	0.743	0.558
	(0.421)	(0.359)	(0.955)	(0.297)	(0.299)	(3.052)	(0.418)	(0.423)	(8.523)	(0.666)	(0.713)	(0.577)
Constant	0.184***		0.416**	0.121***		0.264*	0.063***		0.576	-0.085**	-0.080**	-0.122***
	(0.027)		(0.048)	(0.018)		(0.119)	(0.023)		(0.340)	(0.0339)	(0.039)	(0.027)
Observations	476	476	17	474	474	17	475	475	17	34	34	34
R-squared	0.543	0.615	0.947	0.554	0.613	0.653	0.450	0.535	0.556	0.738	0.742	0.792
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is the growth rate of headcount ratio in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable headcount ration (logarithmic), growth rate of mean consumption and interaction term (headcount ratio and growth rate of mean consumption) refer to 2004-05 for India and 2003-04 for Punjab-Pakistan. The estimation method is ordinary least squares. In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.13: Growth Elasticity of Poverty

	India									Punjab-Pakistan		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HCR initial (log)	1.118***	0.908***	1.343**	1.126***	1.212***	1.337**	1.564***	1.784***	1.523**	0.947***	0.951***	0.765***
	(0.039)	(0.051)	(0.028)	(0.040)	(0.048)	(0.119)	(0.046)	(0.048)	(0.283)	(0.181)	(0.160)	(0.173)
ΔMean consumption (log)	-25.17***	-18.80***	-27.060**	-19.66***	-21.65***	-9.562**	-21.44***	-23.26***	-14.261**	-10.18***	-10.65***	-8.257***
	(1.256)	(1.350)	(1.300)	(0.782)	(0.909)	(2.549)	(0.661)	(0.587)	(3.942)	(3.124)	(2.699)	(2.469)
Constant	2.319***	0.519*	2.864**	1.842***	2.285***	0.922**	2.350***	3.346***	1.653**	0.0526	0.100	-0.235
	(0.159)	(0.297)	(0.143)	(0.110)	(0.192)	(0.278)	(0.111)	(0.151)	(0.504)	(0.327)	(0.276)	(0.339)
Reliability of HCR initial (log)	0.920	0.920	0.99	0.850	0.850	0.97	0.710	0.710	0.92	0.940	0.920	0.90
Reliability of ΔMean consumption (log)	0.916	0.916	0.985	0.895	0.895	0.985	0.771	0.771	0.955	0.940	0.915	0.889
Observations	476	476	17	474	474	17	475	475	17	34	34	34
R-squared	0.719	0.778	0.996	0.734	0.791	0.930	0.832	0.916	0.805	0.662	0.701	0.546
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is logarithmic headcount ratio in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial headcount ratio (logarithmic) and growth rate of mean consumption refer to 2004-05 for India and 2003-04 for Punjab-Pakistan. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficients of initial headcount ratio and growth rate of mean consumption (see section 2.3.2). In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 2.14: Semi-Growth Elasticity of Poverty

	India									Punjab-Pakistan		
	Overall			Rural			Urban			Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HCR initial	0.798***	0.756***	0.763**	0.836***	1.059***	0.780**			0.819**	0.886***	0.966***	0.734***
	(0.017)	(0.027)	(0.017)	(0.017)	(0.011)	(0.087)			(0.131)	(0.122)	(0.107)	(0.123)
ΔMean consumption (log)	-4.209***	-3.776***	-5.083**	-4.632***	-5.916***	-2.708**			-2.352**	-3.882***	-4.299***	-2.925***
	(0.136)	(0.158)	(0.229)	(0.110)	(0.064)	(0.735)			(0.541)	(0.762)	(0.646)	(0.567)
Constant	0.424***	0.413***	0.544**	0.452***	0.591***	0.257*			0.199*	0.072***	0.054**	0.093***
	(0.017)	(0.025)	(0.029)	(0.012)	(0.009)	(0.101)			(0.078)	(0.023)	(0.023)	(0.021)
Reliability of HCR initial (log)	0.920	0.920	0.99	0.850	0.850	0.97	0.710	0.710	0.92	0.940	0.920	0.90
Reliability of ΔMean consumption (log)	0.916	0.916	0.985	0.895	0.895	0.985	0.771	0.771	0.955	0.940	0.915	0.889
Observations	478	478	17	474	474	17			17	34	34	34
R-squared	0.868	0.889	0.996	0.888	0.981	0.901			0.852	0.794	0.852	0.752
State fixed effect	No	Yes	No	No	Yes	No	No	Yes	No			

Notes: The dependent variable is headcount ratio in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial headcount ratio and growth rate of mean consumption refer to 2004-05 for India and 2003-04 for Punjab-Pakistan. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficients of initial headcount ratio and growth rate of mean consumption (see section 2.3.2). In all columns, an observation is a district with the exception of columns 3, 6, and 9, where an observation is a state. In columns 7—8, the regressions are not identified due to the low reliability of initial headcount ration and growth rate of mean consumption. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Chapter 3

A Subnational Analysis of Inequality Convergence: Evidence from India and Pakistan

Abstract Neoclassical growth models predict the convergence of the whole income distribution, rather than just in the first moment. In this paper, I seek an answer to the question of whether income inequalities are persistent over time or converging at the subnational level in India and Pakistan by using household-level data. I find that inequality has increased in India and Pakistan during the last decade. The results reveal a strong indication of inequality convergence within the districts of India and Pakistan. Pakistan appears to converge faster than India. The inequality convergence coefficients are more modest in all specifications when accounting for measurement error. The convergence results are not sensitive to different measures of inequalities. At the current speed of inequality convergence, both countries will reduce inequality to one digit at the end of the United Nations' Sustainable Development Goals 2030.

3.1 Introduction

While income inequality among regions and individuals remains a key developmental challenge, inequality has not received the same attention in the millennium development goals (MDGs), when compared to poverty. However, in the sustainable development goals (SDGs)[1], inequality is adequately covered and integrated into the goals. According to the World Bank (2016), global income inequality slightly decreased from 40.1 in 1993 to 39.3 in 2008. However, this masks regional differences; inequality is decreasing in some regions and countries and increasing in others. It is decreasing in Sub-Saharan Africa, Latin America and the Caribbean, and Eastern Europe and Central Asia. An increasing trend is observed in East Asia and the Pacific, industrialized countries and South Asia.[2] Inequality rose in South Asia from 31.0 to 34.5 between 1993 and 2008. Income inequality increased in all South Asian countries except Bhutan and the Maldives between 1980 to 2015.

The growing inequalities within regions/countries are not helpful for the growth process of any region/country. Inequality can affect the growth process of a region/country due to sociopolitical instability and conflict, which increases uncertainty and reduces savings (Alesina and Perotti 1996). The economic and social outcomes of the persistent inequality are different and differ from country to country (Gruen and Klasen 2008; Dabla-Norris et al. 2015; Hirschman and Rothschild 1973; Ostry et al. 2014; Easterly 2007 & Thorbecke and Charumilind 2002) and sometimes they are more severe in less developed countries when compared to developed countries. The fallout of increasing regional inequalities is more likely to bring about social unrest and conflict in African countries (Østby et al. 2011; Fjelde and Østby 2014) and to create more difficulties for existing regional problems in China (Wei and Kim 2002). The literature on regional inequalities suggests a strong relationship between inequality and political and violent conflict in those countries where ethnic, religious, and racial groups are regionally concentrated (Cederman

[1]The United Nations Sustainable Development Goal 10 aims at “reduce inequalities within and among countries”. For more details on targets and facts see: http://www.un.org/sustainabledevelopment/inequality/.

[2]Inequality has increased in high-income countries due to greater freedom of trade (Bergh and Nilsson 2010), in OECD countries due to globalization from 1970 through 2000 (Dreher and Gaston 2008), in middle income countries due to rent sharing and competition (Reddy et al. 2010) and within developed countries since 1990 (Morelli et al. 2015).

et al. 2011; Stewart 2016). Moreover, inequality divergence will potentially enlarge disparities in human capital outcomes, which in turn will highlight regional imbalance and may harm the growth process. Therefore, it is vital to analyze the persistence of regional inequalities within countries.

Some recent literature identifies that inequality has decreased between certain countries, while it has increased within countries (Moatsos et al. 2014; Chambers and Dhongde 2016; Alvaredo and Gasparini 2015; Ravallion 2018). Both academics and policymakers have developed a considerable interest in discussing the regional distribution of income within countries (Lessmann and Seidel 2017; Smith and Rey 2018). Alvaredo and Gasparini (2015) argue that, although globalization is a significant source of raising inequality, inequality still remains a national concern.

A crucial aspect to consider in discussing inequalities is its subnational dimension, especially in South Asia, a densely populated region of the world. The population share of the South Asian region in the world population increased by roughly 29 percent between 2000 to 2017. Its share of the poor people increased to 33.4 percent from 27.3 percent in world poverty between 1990 to 2013. These figures place this region as one of the most unequal regions of the world. The focus of this study is the two most populous countries of South Asia, namely India and Pakistan. These two countries have performed well in terms of economic growth and poverty reduction during the last decade. The average growth rate of the two countries lies between 5.5 to 6 percent in the previous decade. However, it is unclear whether this income growth benefited all to the same extent or whether income inequality increased at the same time within India and Pakistan.

In this paper, I seek an answer to the question whether the income inequality is persistent or converges at the subnational level in India and Pakistan. For the empirical analysis, this paper's focus is to use the consistent adjusted least squares regression for accounting the measurement error. This is motivated by the fact that in pure cross-sectional regressions, data quality is poor for the observed variable, and measurement error is high in drawing a clear-cut conclusion about the convergence analysis. Temple (1998) is the first who highlights the issue of measurement error in cross-sectional regressions. He finds that the convergence rate is highly sensitive to measurement error in a highly influential paper of Mankiw et al. (1992). Measurement error in the right-hand side variable indicates that the standard error of the initial variable will be larger, making it more difficult to reject the null hypothesis that the speed of convergence is not different from zero. My study takes care of measurement error in inequality convergence by using the consistent adjusted least squares at the subnational level. Moreover, this study also uses the standard growth regression models based on Benabou (1996) and Ravallion (2003) to highlight the measurement error and the robustness of the results.

I use two household surveys to analyze the inequality convergence at the subnational level. For the case of India, I use the much-explored National Sample Survey (NSS). It covers a diverse range of socio-economic indicators for all the regions of India. I use two rounds of NSS data. My analysis focuses on districts of 17 major states of India, as these states are politically and economically more stable when compared to the remaining states. Besides India, Pakistan gives less attention to the analysis of the spatial pattern of inequality. One of the main reasons for this is the scarceness of data at the micro-level. For the analysis, the present study focuses on the Punjab province of Pakistan for two reasons. First, Punjab is the largest province of Pakistan in terms of population, covering 53 percent of Pakistan's total population. Second, Punjab is covered by a unique micro-level dataset. The multiple indicator cluster survey (MICS) is the largest data set representative at the district level to measure inequality in Pakistan. For the purpose of analysis, I use two rounds of MICS. However, in terms of household surveys, Pakistan has other surveys such as Pakistan's social and living standard measurement (PSLM) and the household integrated economic survey (HIES). However, the former is not representative at the district level, and the latter does not have the consumption indicators to measure inequality.

I report three sets of results. First, I find that inequality (Theil index and Gini coefficient) within the two countries generally increased during the previous decade. This increasing trend confirms the pattern of some recent studies (Chambers and Dhongde 2016; Alvaredo and Gasparini 2015; Ravallion 2018). Second, the estimates suggest that there is a convergence in inequality levels in both countries. Convergence is also observed when the sample is disaggregated into rural and urban districts in the two countries. The speed of inequality convergence is higher in Pakistan when compared to India. Third, convergence coefficients do not change much when we take into account the measurement error. In all specifications, the convergence coefficients are smaller when accounting for the measurement error compared to ordinary least square estimates. I find that by accounting the measurement error in India, the convergence coefficient drops by 17 percentage points to 38 percentage points in different specifications. However, the convergence coefficients are stable in Pakistan. I suspect that the measurement error can be a serious threat to the convergence hypothesis when the convergence coefficient is near zero. In addition, these findings are not sensitive to alternative inequality measures and different convergence specifications, i.e., proportionate and absolute.

This essay contributes to the literature on inequality convergence. Compared to the extensive empirical literature on growth convergence, literature on convergence in the income distribution is less often available. Benabou (1996) is the first to analyze the convergence in inequality across countries. His method of analyzing inequality convergence is very similar to the standard test of mean income convergence in growth empirics. He finds evidence for inequality convergence. The empirical literature on inequality convergence can be divided into two strands. According to the first strand, some studies find inequality convergence across the countries (Ravallion 2018; Bleaney and Nishiyama 2003; Alvaredo and Gasparini 2015; Tselios 2009; Chambers and Dhongde 2016), while Gottschalk and Smeeding (2000) do not find any clear link between the initial inequality and overall inequality across the industrialized countries. According to the second strand, there is evidence available in favor of within-country inequality convergence (Marina 2000; Gomes et al. 2007; Lin and Huang 2012; Lin 2011; Ezcurra and Pascual 2009; Panizza et al. 2001; Ho 2015), while Ivanovski et al. (2020) find a mix of evidence in favor of convergence and divergence. My study aligns itself with the second strand of literature.

The contribution of this paper is as follows. First, with regard to development planning, there is a growing interest in the measurement of subnational inequality. Given the economic progress of the last decade, the South Asian region represents an important case study to analyze income inequality. It is one of the regions in which inequality has increased during the last two decades. In South Asian countries, regions with different endowments of resources may result in different output and regional disparities. If these differences in disparities accumulate over the years, they may create social and political unrest, which might become a threat to national integration in India (Alesina and Perotti 1996; Benhabib and Rustichini 1996; Chowdhury 2003). Das et al. (2010) emphasize that, due to the concerns of social resentment and political unrest, inequality has moved to the top of the political agenda in recent times. The persistence or further increase in inequality can destabilize the growth process by hindering the opportunities of human capital formation and intergenerational mobility. Reducing inequality is not only beneficial for the people within countries, but also necessary for the political peace and stability of the region. These factors make the South Asian region a critical case study to examine the persistence of inequality over time.

Moreover, a subnational analysis of inequality convergence contributes to a more comprehensive understanding of the relationship between changes in inequality with its initial level in the developing world. It will provide incentives for national governments to design and implement inequality-reducing strategies. Second, being the two most populous countries in the South Asian region, this study will provide a guideline to policymakers about whether the South Asian region is on track to reduce income inequalities at the subnational level. By considering the current absolute inequality convergence (Theil index and Gini coefficient), the two countries will significantly improve the gap between poor and rich people by the end of 2030. I find that inequality will be in one-digit number in both countries at the end of SDGs 2030. Further, the strength of my analysis is the application of a novel approach which accounts for measurement error. I use consistent adjusted least squares to analyze the inequality convergence, which is also applicable to other empirical convergence analyses. While accounting for measurement error, the convergence coefficients are slightly more modest. Finally, it is also essential that focusing on the inequality levels within the two selected countries improves the reliability of results and adequately deals with heterogeneity in the measurement of income inequality. Intra-country analysis of inequality provides a more homogenous data set for conducting tests on inequality convergence.

The rest of the study is organized as follows. In the next section, I present the conceptual framework of inequality convergence. In section 3, I discuss the problem of measurement error and consistent adjusted least squares. The data description and the measurement of inequality is explained in section 4. In section 5, I present the empirical results of inequality convergence. Finally, section 6 concludes.

3.2 Conceptual Framework

The empirical implication of the neoclassical growth models focused on the convergence in its first moment. However, neoclassical models yield the convergence of the whole distribution (Benabou 1996 & Ravallion 2018). Countries with the same fundamentals will tend to evolve toward a common distribution, with falling inequality in high inequality countries, and rising inequality in low inequality countries. Tselios (2009) explained two possible reasons for inequality convergence. First, when the capital flow proceeded from developed countries (low inequality) to less developed countries (high inequality), the disparities reduced and as a result both income and inequality converged. Second, inequality convergence is observed when individuals migrate in search of better jobs. They usually move to high wage regions with less inequality. Besides this, Gallup (2012) presented a different way of understanding inequality convergence. He argued that democratic participation increases as the income level rises, so the greater political activism increases the rate of convergence through redistributive policies.

The most straightforward test to check the convergence in income inequality is analogous to the standard test to check the mean income convergence. It analyzed the correlation between the growth rate of inequality and its initial level. Benabou (1996) was the first to examine the convergence in inequality across countries. This study analyzed inequality convergence by following the approach of Benabou (1996) and Ravallion (2003). The test equation of inequality convergence, on the basis of the aforementioned studies, is based on the Gini coefficient:

$$\Delta Gini_{it} = \delta_i + \beta_i Gini_{it-1} + \gamma_{it} \tag{3.1}$$

The left-hand side variable is the annual change in the Gini coefficient. The explanatory variable is the Gini coefficient and for the convergence condition, $\beta<0$ in the country i and time t. Ravallion (2003) used the same equation to test the convergence in the Gini coefficient as well as using the logarithmic version of this equation.

$$\Delta lnGini_{it} = \alpha_i + \beta_i lnGini_{it-1} + \sigma_{it} \tag{3.2}$$

Where the dependent variable is the annual growth rate of the Gini coefficient and convergence condition is β<0 in country i and time t.

Benabou (1996) found evidence of convergence in various data sets and different time periods across countries. Ravallion (2003) also analyzed inequality convergence by using two different data sets across eighty-three countries. He observed negative and statistically significant coefficient of convergence. Ravallion (2003) also examined the convergence across the countries and found a strong indication of inequality convergence for both the linear and log specification. In this study, I apply both equation 3.1 and 3.2 to my study.

3.3 Empirical Approach

3.3.1 Basic Setup

For analyzing the inequality convergence, the regression of interest is

$$g(\overline{X}_i) = \log \overline{X}_{i1} - \log \overline{X}_{i0} = \alpha + \beta \log \overline{X}_{i0} + u_i \tag{3.3}$$

where $i = 1, ..., I$ indexes districts and 0 and 1 denote baseline and endline periods.

$\overline{X}_{it}$ is an inequality measure for district i in period t (=0, 1) calculated from unit-level observations, which we index by j:

$$\overline{X}_{it} = \frac{1}{J_{it}} \sum\nolimits_{j=1}^{J_{it}} X_{ijt}$$

There are J_{it} unit level observations in the sample for district i and year t. Following Temple (1998), equation 3.3 may be re-written as

$$\log \overline{X}_{i1} = \alpha + (1+\beta) \log \overline{X}_{i0} + u_i \tag{3.4}$$

Given that $\overline{X}_{i0}$ is the inequality measure of a (small) sample, it is clear that

$$\overline{X}_{i0} = \mu_{i0} + v_i$$

where μ_{i0} denotes the true mean of X_{ij0} and v_i is the sampling error of $\overline{X}_{i0}$ relative to μ_{i0}.

I am interested in the true value of b in the regression.

$$\log \mu_{i1} = a + (1+b) \log \mu_{i0} + u_i$$

Suppose that $0 > b > -1$, i.e., the process governing μ_{it} is not a random walk but a stationary process with some persistence. The OLS estimate of (1+β), (1+$\widehat{\beta}$), obtained from estimating (3.4) will be biased downward relative to $(1+b)$ whenever $V(v_i) > 0$, which implies that $\widehat{\beta}$ will be biased downward relative to b. To illustrate, suppose for example that $b = 0$, i.e., there is no inequality convergence. The downward bias of $\widehat{\beta}$ may lead us to conclude that there is inequality convergence.

3.3.2 Accounting for measurement error in regressions of inequality convergence

If the measurement error of $\log \overline{X}_{i0}$ is known, the bias of the OLS estimate of (1+β) in equation (3.4) can be removed. When the variance of v_i is known, a consistent estimator of (1+β) is available through the so-called consistent adjusted least square (CALS) estimator, which has been introduced for more general cases by Kapteyn and Wansbeek (1984). The present case of a single contaminated regressor is dealt with in detail in Wansbeek and Meijer (2000) (For more details, see section 2.3.3).

For the estimation procedure, I need the reliability coefficient of the regressor $\log \overline{X}_{i0}$ in equation (3.4), which can be written as

$$1 - \frac{\text{Measurement Error Variance}}{\text{Total Variance}}.$$

In simple words, I need the measurement error variance and total variance of $\log \overline{X}_{i0}$. In this case, the total variance is trivial, it is simply the sample variance of $\log \overline{X}_{i0}$, where the variance is taken over the I observations of $\overline{X}_{i0}$.

The measurement error variance, in this case, comes from the variance of the sampling error. The additional complication here relative to poverty measures is that each entropy index is a non-linear function of two or three different statistics of the data, which makes estimation of the sample variance according to the techniques described in section 2.3.2 inconsistent.

The existing literature outlines several existing methods for the calculation of sampling variance of inequality measures (Ogwang 2000; Karagiannis and Kovacevic 2000; Karoly 1989; Mills and Zandvakili 1997; Biewen 2002; Thistle 1990; Cowell 1989). However, these papers do not discuss the distinct feature of complex survey data (clustering, stratification, and probability weighting). It is well known that, in the case of complex survey data, these features of the data may have a key impact on the sampling variability of statistics. Biewen and Jenkins (2006) explain in detail how to calculate the sampling variance for the Generalized entropy and Atkinson class of inequality measures. They calculate the sampling variance based on Taylor-series linearization methods combined with a result from Woodruff (1971) (for detail see Biewen and Jenkins (2006)). For the analysis, I calculate the sampling variance for the Theil index through the method of Biewen and Jenkins (2006). For the case of the Gini coefficient, the sampling variance is calculated by following Kovacevic and Binder (1997). Their method is also based on the Taylor-series linearization method.

3.3.3 Data Contamination

The estimation of welfare indices from household data sets is known to be sensitive in the presence of extremely high income (Cowell and Victoria-Feser 1996; Cowell and Victoria-Feser 2002 and Cowell and Victoria-Feser 2001). It is especially problematic to measure inequality because many indicators of inequality are influenced by data contamination at the tails of the distribution and thus potentially biased. A single outlier in the distribution can drive the inequality index to become arbitrarily very small or large (Van Kerm et al. 2007). There are many reasons for the presence of extreme observation in income distribution. They may be due to the reporting error or miscoding of the decimal separator. Even if there is no data contamination and all the extreme incomes are real, still the extreme values will bias the inequality index. In this case, the sampling variability of the inequality index can be very large because of the sparseness of high and low incomes in the total distribution. For the calculation of robust estimates, the distribution must not have any extreme values. The simple strategy to prevent the distribution from extreme income is the trimming of the entire distribution. Cowell and Victoria-Feser (2006) discuss in detail how the trimming strategy is used to create 'robust' welfare comparisons in the distributional analysis. In this study, I applied the one percent trimming to both ends to calculate the Theil index and the Gini coefficient.

3.4 Data Description

To compute and analyze the inequality measures, I use two household data sets. In the case of India, I use the National Sample Survey (NSS). The NSS is a household survey covering the various socio-economic indicators from all geographic regions of India. I use two rounds of NSS (61^{st} in 2004-05 and 68^{th} in 2011-12). The focus of my analysis is on the 17 major states of India. The sample size is 249,321 in the 61st round of NSS and 203,635 households in the 68th round of NSS. In the case of Punjab-Pakistan, I use the Multiple Indicator Cluster Survey (MICS). The MICS is a household survey covering more than 100 indicators from all the geographic regions of Punjab-Pakistan. For the purposes of analysis, this study uses two rounds of MICS (1^{st} in 2003-04 and 3^{rd} in 2010-11). The total sample size of MICS 2011 is 102,545 households, and MICS 2003 is 30,932 households, respectively. The MICS were planned, designed, and implemented by the Bureau of Statistics, Punjab-Pakistan, with the help of the Pakistan Bureau of Statistics (PBS) and the United Nations Children's Fund (UNICEF). For the calculation of the value of commodities, this study uses the price data from the Bureau of Statistics (BOS), Punjab-Pakistan. The reason for this is that the MICS 2011 did not report the prices of the commodities. There is no such issue with the MICS 2003, but for the sake of comparability, I also apply the same exercise with the MICS 2003. The BOS encompasses the data from different regions of Punjab-Pakistan. To calculate inequality measures, the focus of this study is to choose the consumption-based indicators instead of the income-based. Consumption is usually regarded as a better measure of current welfare than income on both theoretical and practical grounds, especially in developing countries (Deaton and Zaidi 2002). The income may fluctuate highly among those households who are employed in the agriculture sector or self-employed, and consumption seems more stable in any situation. For these reasons, while I will refer to the main outcome variable as income inequality, statistics are constructed over the distribution of consumption expenditures. I measure inequality by using the Theil index. The advantage of this over the Gini coefficient is that it can easily be decomposed when inequality is measured in groups. In a population, the total inequality depends on inequality across the groups and inequality within groups. No such simple decomposition is available for the Gini coefficient. However, this study also uses the measures of inequality, like the Gini coefficient (the most commonly used measure of inequality in the literature), mean logarithmic deviation, and coefficient of variation, to check the robustness of my results.

3.5 Empirical Results

3.5.1 Summary Statistics

The summary statistics in Table 3.5 show that inequality slightly increased in the two countries. The Theil index increased from 11.4 to 12.0 in India, while it increased from 16.8 to 23.8 in Pakistan. The Gini coefficient increased from 24.6 to 25.3 in India, while in Pakistan, it increased from 31.5 to 35.4. In rural districts of India, the mean Theil index and Gini coefficient lies below the national averages. The Theil index increases from 8.7 to 9.3, while the Gini coefficient increased from 21.5 to 22.3. In urban districts of India, the averages of both indexes lie above the national averages. I find that the Gini coefficient is more stable for urban districts in India between 2004-05 and 2011-12, and the coefficient undergoes a slight increase from 27 to 27.2. In Pakistan, I also find that the Theil index and Gini indices increased in rural and urban districts. In rural districts, the Theil index increased from 16.6 to 23.3 while in urban districts, it increased from 16.7 to 24 between 2003-04 and 2010-11. The Gini coefficient also increased from 31.3 to 34.9 in rural districts of Punjab-Pakistan while it increased from 31.1 to 36.2 in urban districts. In short, income inequality (Theil index and Gini coefficient) increased at the subnational level in both India and Pakistan. This increasing trend is consistent with findings of some recent literature (Alvaredo and Gasparini 2015; Chambers and Dhongde 2016; Ravallion 2018).

3.5.2 Inequality Convergence

This section is divided into two parts. In the first section, I discuss the results of proportionate inequality convergence. In the second section, I discuss the results of absolute inequality convergence. Table 3.1 provides the estimates of the proportionate Theil convergence by applying the consistent adjusted least squares estimates to India and Pakistan. In Table 3.1, the convergence coefficient is $1+\beta$. The convergence coefficient and reliability coefficient of the initial Theil index are reported in the second half of Table 3.1.

I find strong evidence of proportionate Theil convergence at the national and state levels in India. In columns 1 and 2, the coefficient of Theil convergence is around 5 percent, showing that a 1 percent increase in the initial Theil index decreases the growth rate of the Theil index by 0.5 percent in India. In column 2, which includes state fixed effects, the convergence coefficient does not change much, when compared to the national level. Finally, I also analyze the convergence in the Theil index at the rural and urban levels of India. I find a higher speed of proportionate convergence at the rural districts compared to urban districts. In rural districts, the convergence coefficient is 7 percent at the national level. When the state fixed effect is included, it rises to 8 percent. However, the convergence coefficient is stable in the urban districts of India. It remains at around 6.1 percent to 6.3 percent at the national and state levels in columns 5 and 6. In Pakistan's case, the coefficient of proportionate Theil convergence is 11.6 percent, showing that a 1 percent increase in the initial Theil index decreases the growth of the Theil index by 11.6 percent. In rural and urban districts, the evidence of Theil convergence is also observed. The coefficient of Theil convergence remains stable across all cases in Pakistan. In each case, Pakistan's speed of convergence is twice as fast as India's. This might be due to the fact that Punjab-Pakistan is a much smaller unit compared to India. It seems that Punjab reflects greater homogeneity in the economic fundamentals than India, while India is a large unit with more disparities in economic fundamentals.

In order to account for any measurement error in inequality convergence, I present the estimates of proportionate Theil convergence by using the ordinary least square (OLS) in Table 3.6 in the appendix. The results reveal the presence of Theil convergence in India and Pakistan. Using OLS, I find that the convergence coefficient is higher in India, while it is stable in Pakistan. I also find that the convergence coefficient varies from 17 to 38 percentage points by using two approaches. Based on CALS and OLS estimates, I suspect that measurement error can be a serious threat to the convergence validity when the convergence coefficient is near zero. In the case of Punjab-Pakistan, the results are not different from the CALS regressions. The coefficient varies from 11.5 percent to 11.7 percent in all Pakistan cases, while it increases from 11.4 percent to 11.6 percent in the CALS regression. I plot the annualized growth rate in the Theil index against the initial value of the Theil index in Figure 1(a)-1(f) in the appendix. These figures also present the evidence for proportionate convergence in the Theil index.

Table 3.1: Proportionate Theil Convergence

	India						Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Theil Index (log)	0.634**	0.648**	0.524**	0.455**	0.575**	0.557**	0.187	0.204	0.198
	(0.039)	(0.051)	(0.047)	(0.069)	(0.064)	(0.084)	(0.097)	(0.109)	(0.110)
Constant	-0.769**		-1.130**		-0.878**		-1.113**	-1.100**	-1.089**
	(0.090)		(0.122)		(0.138)		(0.182)	(0.205)	(0.208)
Convergence coefficient	-0.052***	-0.050***	-0.068***	-0.078***	-0.061***	-0.063***	-0.116***	-0.114***	-0.115***
	(0.006)	(0.007)	(0.007)	(0.010)	(0.009)	(0.012)	(0.014)	(0.016)	(0.016)
Reliability of Theil Index (log)	0.817	0.817	0.750	0.750	0.632	0.632	0.97	0.96	0.90
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.406	0.458	0.258	0.327	0.211	0.278	0.106	0.102	0.100
State fixed effect	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is logarithmic Theil index in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial Theil index (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial Theil index (see section 3.3.2). In all columns, an observation is a district. I add state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.2: Proportionate Gini Convergence

	India						Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Gini coefficient (logarithmic)	0.578**	0.560**	0.461**	0.374**	0.417**	0.359**	0.187	0.201	0.191
	(0.034)	(0.041)	(0.040)	(0.052)	(0.047)	(0.055)	(0.093)	(0.105)	(0.103)
Constant	-0.570**		-0.801**		-0.765**		-0.824**	-0.822**	-0.796**
	(0.049)		(0.063)		(0.064)		(0.110)	(0.125)	(0.124)
Convergence coefficient	-0.060***	-0.063***	-0.077***	-0.089***	-0.083***	-0.092***	-0.116***	-0.114***	-0.116***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.017)	(0.016)	(0.017)
Reliability of Gini coefficient	0.92	0.92	0.868	0.868	0.86	0.86	0.975	0.966	0.931
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.400	0.445	0.243	0.321	0.159	0.228	0.115	0.106	0.103
State fixed effect	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is logarithmic Gini coefficient in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial Gini coefficient (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial Gini coefficient (see section 3.3.2). In all columns, an observation is a district. I add state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

The main focus of this study is to analyze convergence in terms of the Theil index. However, I also estimate convergence in terms of the Gini coefficient in India and Pakistan, as Gini is the most frequently used measure of inequality in previous studies. Table 3.2 provides the CALS estimates of proportionate Gini convergence. In this table, the Gini convergence coefficient is $1+\beta$. For accounting the measurement error, the reliability coefficient of the initial Gini coefficient is estimated. This study finds the presence of proportionate Gini convergence in India. The coefficient of proportionate Gini convergence is around 6 percent at both the national and state levels in India. The Gini convergence is also observed in the rural and urban districts of India. This study finds a very similar coefficient of proportionate Gini convergence to the proportionate Theil convergence which I find in the case of Pakistan. The coefficient of proportionate Gini convergence is 11.6 percent, showing that a 1 percent increase in the initial Gini coefficient decreases the Gini coefficient's growth by 11.6 percent. In rural and urban districts, convergence is also found, and the coefficient remains stable across all cases in Punjab-Pakistan. The speed of the Gini convergence is higher in Punjab-Pakistan compared to India, and the same can be said for the Theil convergence.

For comparison, the OLS estimates of the proportionate Gini convergence are presented in Table 3.7 in the appendix. Here I observe the proportionate Gini convergence in the two countries. The coefficients were found to be higher by using the OLS in all cases of India when compared to CALS estimates. The proportionate convergence coefficient declines in the range of 3 to 11 percentage points in Table 3.2 when compared to OLS estimates in Table 3.7. However, the reduction in the Gini coefficient is smaller than that in the Theil index. I plot the Gini coefficient's annualized growth rate against the initial value of the Gini coefficient in Figure 2(a)-2(f) in the appendix. These figures also show evidence of proportionate convergence in the Gini coefficient.

I report the estimate of absolute inequality convergence, based on the Benabou (1996) approach. In Table 3.3, I find an indication of absolute Theil convergence by using the CALS regression. The convergence coefficients in columns 1 and 2 are very similar across the national and state level in India. The speed of convergence is higher at the state level in rural districts of India compared to overall and urban districts. Absolute Theil convergence is observed, and the convergence coefficients are stable across all cases of Pakistan. Besides absolute Theil convergence, I also examine the absolute Gini convergence in two countries. I find evidence of absolute Gini convergence in all cases of India and Pakistan, and my results are reported in Table 3.4. For comparison purposes of Tables 3.3 and 3.4, OLS estimates of the same equations are estimated, and the results are presented in Tables 3.9 and 3.10 in the appendix. In India, the convergence coefficients vary in the range of 20 to 40 percentage points. However, convergence coefficients are stable in Pakistan across different specifications. Figure 3(a)-3(f) plots the annual change in the Theil index against the initial value of the Theil index. In Figure 4(a)-4(f), I plot the annualized change in the Gini coefficient against the initial Gini coefficient. These figures also support the evidence of absolute convergence in the Theil index.

I also report the convergence results of other inequality measures such as the mean logarithmic deviation and the coefficient of variation in Tables 3.10–3.17 in the appendix. These two measures also confirm the evidence of inequality convergence in India and Pakistan. The pattern of these results is similar to the Theil and Gini coefficient. This study observes the inequality convergence in two countries for all measures of inequality. The results of this study are consistent with the previous literature on within country inequality convergence (Gomes et al. 2007; Ezcurra and Pascual 2009; Ivanovski et al. 2020). The inequality convergence coefficients are on average higher at the subnational level in India and Pakistan compared to the across countries studies. This could be due to the fact that within countries regions/districts have more similar sources of economic growth when compared to results across countries. This study highlights the issue of measurement error in inequality. If we do not adequately deal with the measurement error in the initial variable then it could be a serious threat to the validity of the convergence hypothesis. The present study observes that the convergence coefficient fell up to 40 percentage points while accounting for the measurement error.

The results of inequality convergence are inline with the findings of Das et al. (2010). They find the Gini convergence among 14 major states of India by using the panel unit root approach. However, this study considers the districts of India by using the cross-sectional approach. This study finds the Gini and Theil convergence among India's districts, and convergence is also observed within India's states. Moreover, convergence is observed with proportionate and absolute approaches, which explains that inequality in income distribution does not only decrease in overall districts of India but also the speed of convergence is faster in those districts who have higher initial inequality. The major difference between the present study and Das et al. (2010) is the methodology of inequality convergence. The former use consistent adjusted least square to analyze the inequality convergence while later use panel unit root.

Table 3.3: Absolute Theil Convergence

	India						Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Theil Index	0.705**	0.713**	0.506**	0.359**	0.662**	0.624**	0.227	0.249	0.259
	(0.049)	(0.059)	(0.065)	(0.085)	(0.075)	(0.093)	(0.145)	(0.156)	(0.185)
Constant	0.040**		0.050**		0.048**		0.199**	0.192**	0.196**
	(0.006)		(0.006)		(0.010)		(0.026)	(0.027)	(0.033)
Convergence coefficient	-0.042***	-0.041***	-0.071***	-0.092***	-0.048***	-0.054***	-0.110***	-0.107***	-0.106***
	(0.007)	(0.008)	(0.009)	(0.012)	(0.011)	(0.013)	(0.021)	(0.022)	(0.026)
Reliability of Theil Index	0.817	0.817	0.750	0.750	0.632	0.632	0.97	0.96	0.90
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.343	0.402	0.145	0.233	0.207	0.284	0.074	0.076	0.063
State fixed effect	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is Theil index in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial Theil index refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial Theil index (see section 3.3.2). In all columns, an observation is a district. I add state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.4: Absolute Gini Convergence

	India						Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Gini coefficient	0.622**	0.611**	0.477**	0.365**	0.450**	0.390**	0.195	0.209	0.216
	(0.038)	(0.045)	(0.045)	(0.057)	(0.050)	(0.058)	(0.105)	(0.116)	(0.126)
Constant	0.100**		0.120**		0.151**		0.293**	0.283**	0.295**
	(0.009)		(0.010)		(0.014)		(0.033)	(0.037)	(0.040)
Convergence coefficient	-0.054***	-0.056***	-0.075***	-0.091***	-0.079***	-0.087***	-0.115***	-0.113***	-0.112***
	(0.005)	(0.006)	(0.006)	(0.008)	(0.007)	(0.008)	(0.016)	(0.016)	(0.016)
Reliability of Gini coefficient	0.92	0.92	0.868	0.868	0.86	0.86	0.975	0.966	0.931
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.385	0.431	0.214	0.303	0.163	0.237	0.100	0.096	0.089
State fixed effect	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is Gini coefficient in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial Gini coefficient refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial Gini coefficient (see section 3.3.2). In all columns, an observation is a district. I add state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

3.6 Conclusion

Neoclassical models imply convergence of the entire distribution, not just the mean income levels. In this paper, I analyzed the convergence in income inequality at the subnational level in India and Pakistan by using the consistent adjusted least squares regression. This study finds that inequalities are not persistent at the subnational levels in India and Pakistan. I find strong evidence of proportionate and absolute inequality convergence. Moreover, convergence results are not sensitive to different measures of inequality. In Pakistan, the speed of inequality convergence is higher and more consistent across different specifications when compared to India. This might be because India is a large and more diverse country than Pakistan with different economic fundamentals of each state. At the same time, Punjab-Pakistan is a relatively small and more homogenous region with a homogeneous economic context. Keeping in view the SDGs 2030, the performance of the two countries seems satisfactory in inequality reduction. The coefficient of inequality will be in the one-digit range at the current speed of inequality convergence in India and Pakistan. Further exploration of the districts' specific characteristics in order to explain the emergence of inequality convergence may be exciting and useful. Moreover, India has initiated different economic reforms to liberalize its economy since the 1990s. Under the decentralization reform initiated in 2000, Pakistan has also completed two consecutive tenures of local governments during the last decade. How much these policies contributed to the high rate of inequality convergence in each country would be an interesting question for future research.

Appendix

Figure 1(a):
Proportionate Theil convergence: Overall India

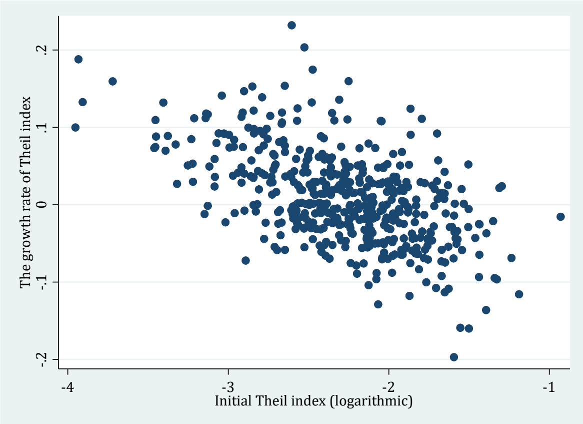


Figure 1(b):
Proportionate Theil convergence: Rural India

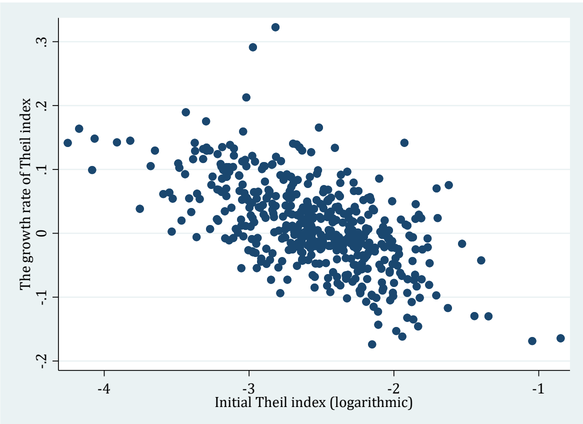


Figure 1(c):
Proportionate Theil convergence: Urban India

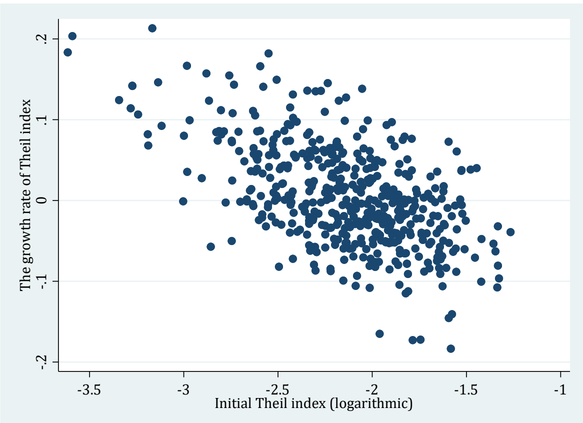


Figure 1(d):
Proportionate Theil convergence: Overall Pakistan

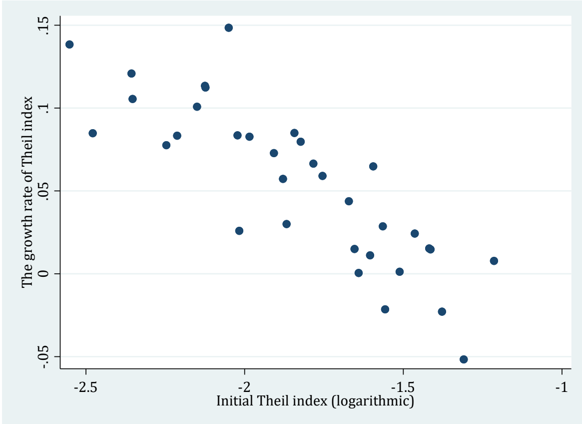


Figure 1(e):
Proportionate Theil convergence: Rural Pakistan

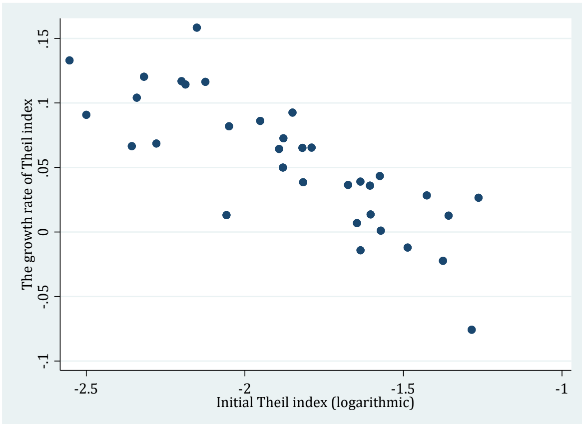


Figure 1(f):
Proportionate Theil convergence: Urban Pakistan

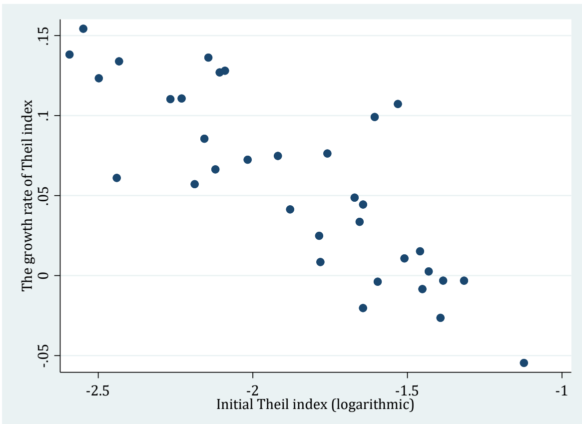


Figure 2(a):
Proportionate Gini convergence: Overall India

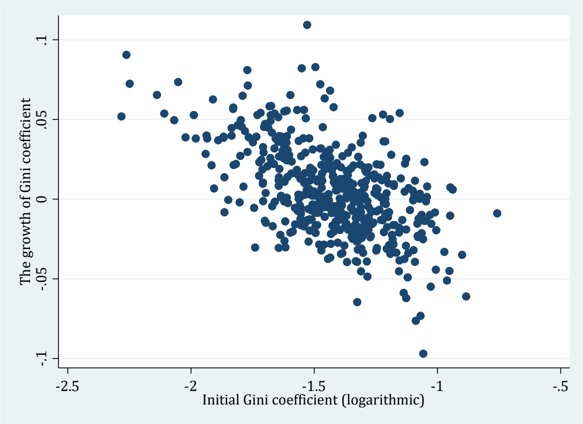


Figure 2(d):
Proportionate Gini convergence: Overall Pakistan

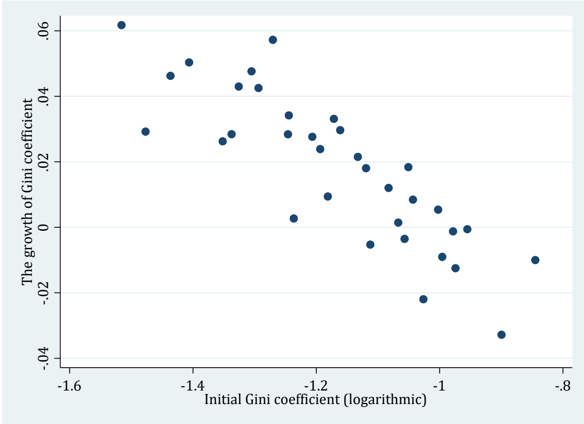


Figure 2(b):
Proportionate Gini convergence: Rural India

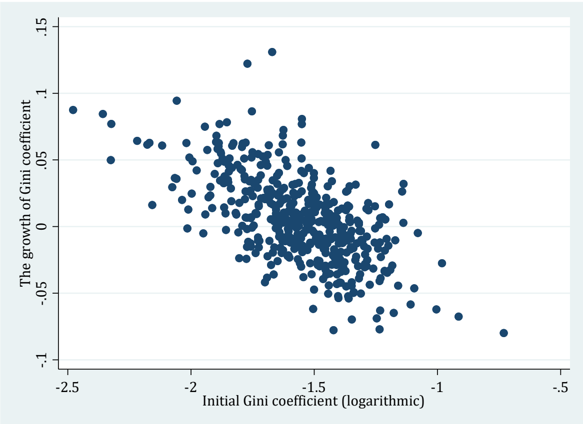


Figure 2(e):
Proportionate Gini convergence: Rural Pakistan

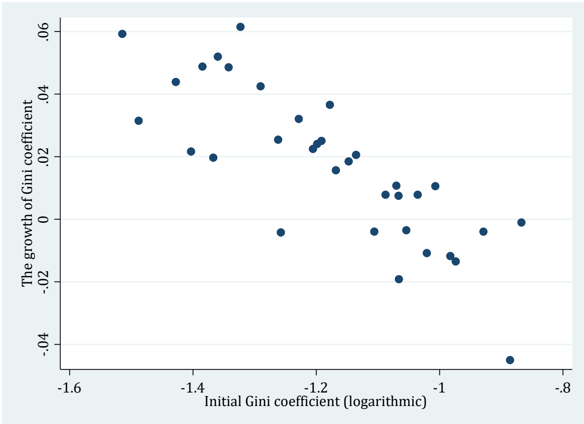


Figure 2(c):
Proportionate Gini convergence: Urban India

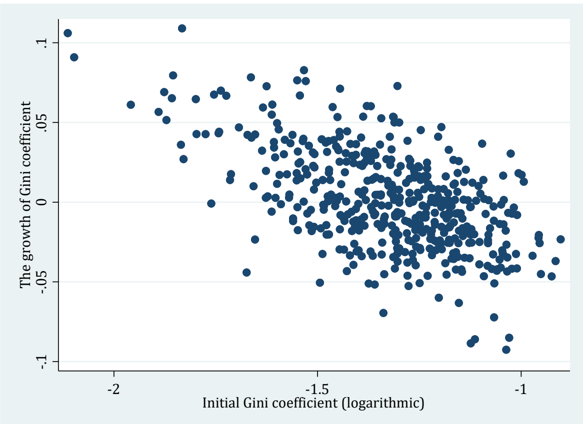


Figure 2(f):
Proportionate Gini convergence: Urban Pakistan

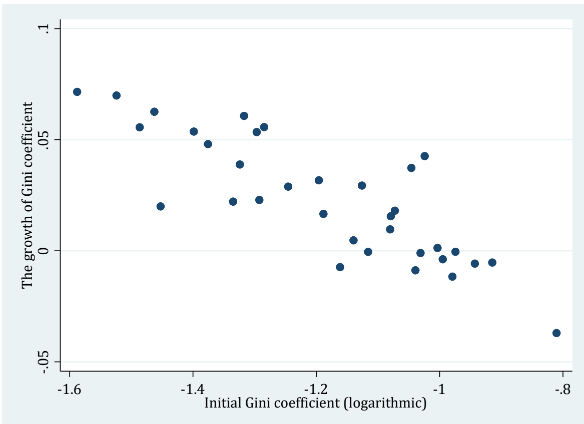


Figure 3(a):
Absolute Theil convergence: Overall India

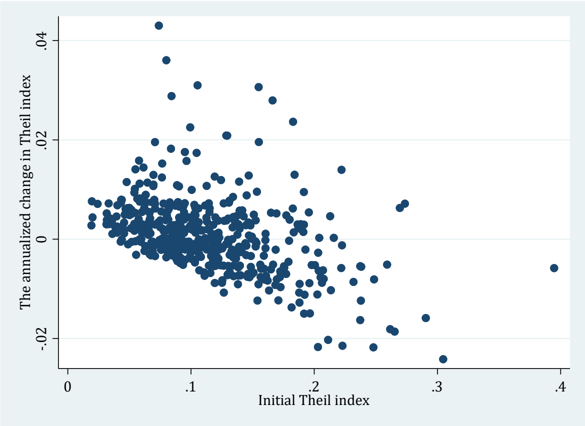


Figure 3(d):
Absolute Theil convergence: Overall Pakistan

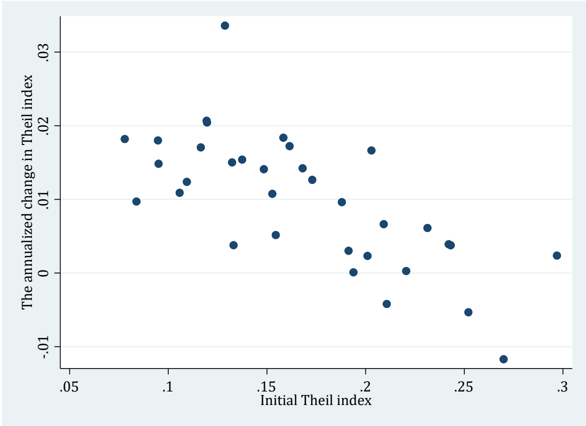


Figure 3(b):
Absolute Theil convergence: Rural India

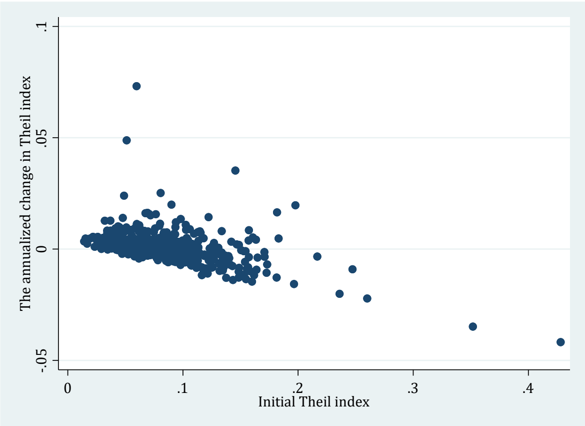


Figure 3(e):
Absolute Theil convergence: Rural Pakistan

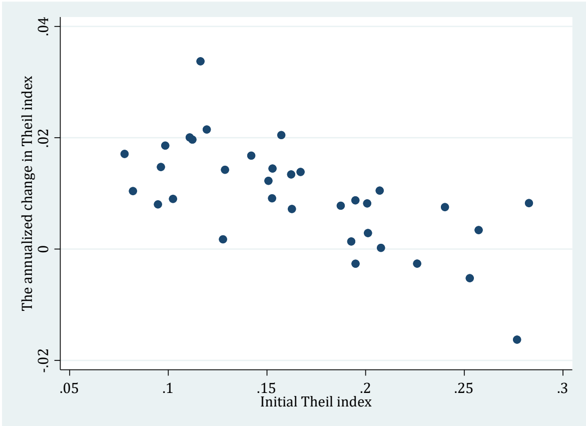


Figure 3(c):
Absolute Theil convergence: Urban India

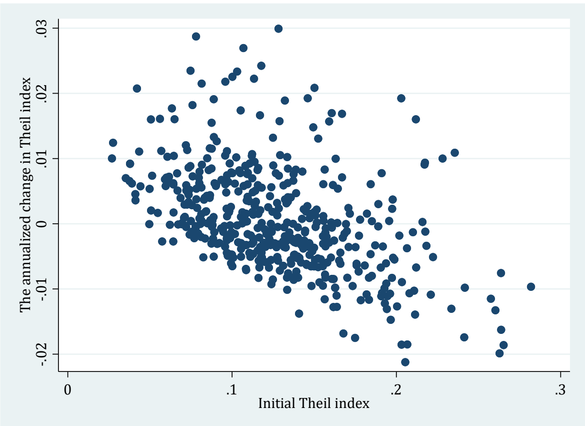


Figure 3(f):
Absolute Theil convergence: Urban Pakistan

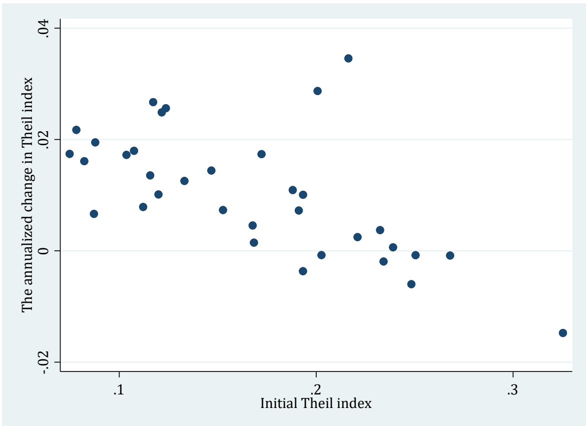


Figure 4(a):
Absolute Gini convergence: Overall India

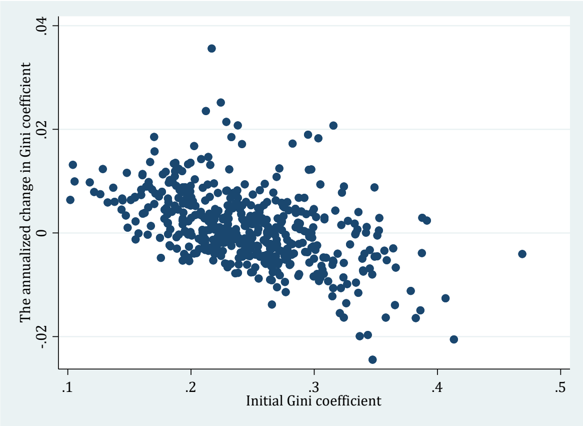


Figure 4(d):
Absolute Gini convergence: Overall Pakistan

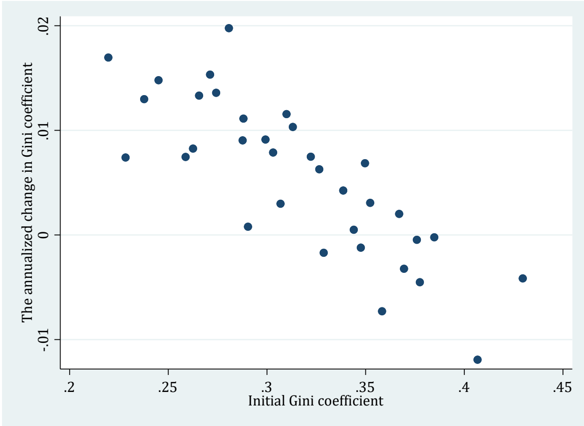


Figure 4(b):
Absolute Gini convergence: Rural India

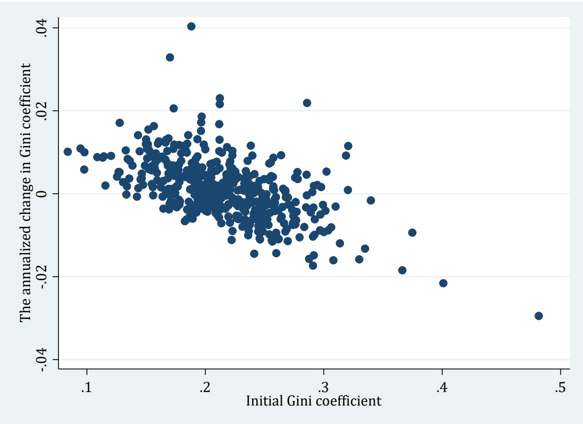


Figure 4(e):
Absolute Gini convergence: Rural Pakistan

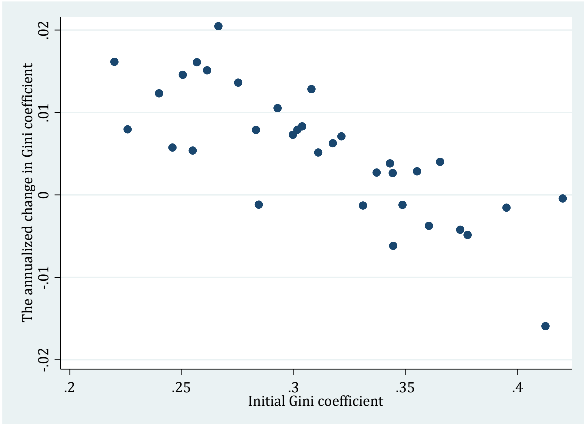


Figure 4(c):
Absolute Gini convergence: Urban India

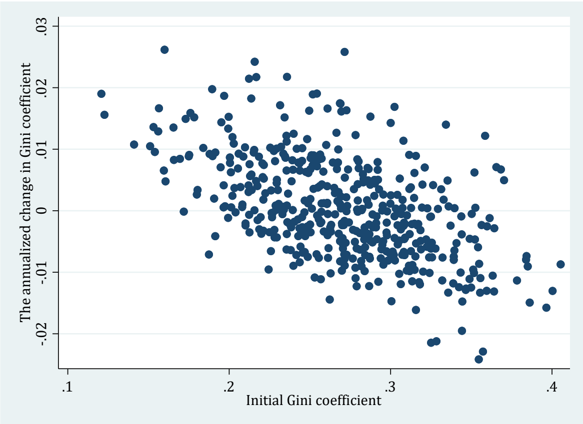


Figure 4(f):
Absolute Gini convergence: Urban Pakistan

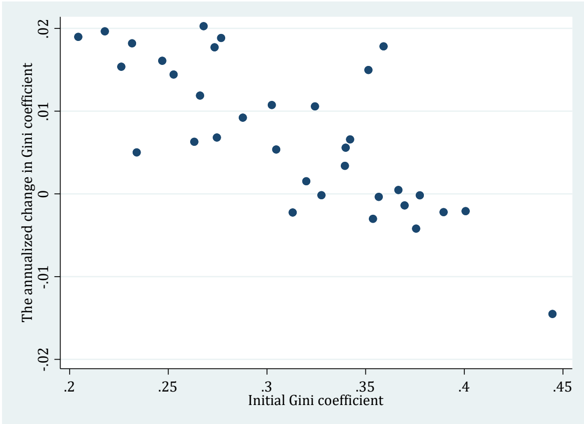


Table 3.5: Summary Statistics of Inequality Measures

	India					
	Districts	Observations	Mean	SD	Min	Max
Overall						
Theil Index 2004	478	199,588	0.114	0.052	0.019	0.395
Theil Index 2012	478	161,084	0.120	0.057	0.033	0.375
Gini Coefficient 2004	478	199,588	0.246	0.056	0.102	0.469
Gini Coefficient 2012	478	161,084	0.253	0.054	0.142	0.466
Rural						
Theil Index 2004	474	126,986	0.087	0.043	0.014	0.428
Theil Index 2012	474	95,269	0.093	0.050	0.030	0.572
Gini Coefficient 2004	474	126,986	0.215	0.048	0.084	0.482
Gini Coefficient 2012	474	95,269	0.223	0.047	0.130	0.471
Urban						
Theil Index 2004	477	72,602	0.126	0.046	0.027	0.282
Theil Index 2012	477	65,815	0.131	0.054	0.038	0.338
Gini Coefficient 2004	477	72,602	0.270	0.051	0.121	0.405
Gini Coefficient 2012	477	65,815	0.272	0.053	0.138	0.452
	Pakistan					
Overall						
Theil Index 2003	34	30,758	0.168	0.057	0.078	0.297
Theil Index 2011	34	102,545	0.238	0.047	0.152	0.364
Gini Coefficient 2003	34	30,758	0.315	0.052	0.220	0.430
Gini Coefficient 2011	34	102,545	0.354	0.032	0.280	0.419
Rural						
Theil Index 2003	34	18,560	0.166	0.057	0.078	0.283
Theil Index 2011	34	60,498	0.233	0.051	0.140	0.352
Gini Coefficient 2003	34	18,560	0.313	0.053	0.220	0.420
Gini Coefficient 2011	34	60,498	0.349	0.035	0.276	0.417
Urban						
Theil Index 2003	34	12,198	0.167	0.063	0.075	0.325
Theil Index 2011	34	42,047	0.240	0.063	0.134	0.458
Gini Coefficient 2003	34	12,198	0.311	0.059	0.204	0.445
Gini Coefficient 2011	34	42,047	0.362	0.041	0.269	0.484

Notes: Authors' calculation based on NSS and MICS data

Table 3.6: Proportionate Theil Convergence: Ordinary Least Squares Estimation

	India						Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Theil Index (logarithmic)	0.518**	0.473**	0.393**	0.281**	0.363**	0.295**	0.182	0.196	0.181
	(0.033)	(0.041)	(0.036)	(0.043)	(0.042)	(0.047)	(0.094)	(0.116)	(0.090)
Constant	-1.033**		-1.465**		-1.332**		-1.122**	-1.114**	-1.120**
	(0.078)		(0.095)		(0.091)		(0.174)	(0.218)	(0.176)
Convergence coefficient	-0.069***	-0.075***	-0.087***	-0.103***	-0.091***	-0.101***	-0.117***	-0.115***	-0.117***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.013)	(0.017)	(0.013)
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.332	0.389	0.194	0.287	0.133	0.216	0.103	0.099	0.091
State Fixed effect	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is logarithmic Theil index in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial Theil index (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is ordinary least squares. In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.7: Proportionate Gini Convergence: Ordinary Least Squares Estimation

	India						Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Gini coefficient (logarithmic)	0.532**	0.495**	0.400**	0.299**	0.359**	0.295**	0.182	0.194	0.178*
	(0.031)	(0.039)	(0.034)	(0.040)	(0.041)	(0.046)	(0.094)	(0.115)	(0.087)
Constant	-0.636**		-0.896**		-0.842**		-0.829**	-0.830**	-0.812**
	(0.046)		(0.054)		(0.055)		(0.109)	(0.135)	(0.106)
Convergence coefficient	-0.067***	-0.072***	-0.086***	-0.100***	-0.092***	-0.101***	-0.117***	-0.115***	-0.117***
	(0.004)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.013)	(0.016)	(0.012)
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.368	0.416	0.211	0.301	0.137	0.213	0.112	0.102	0.096
State Fixed effect	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is logarithmic Gini coefficient in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial Gini coefficient (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is ordinary least squares. In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.8: Absolute Theil Convergence: Ordinary Least Squares Estimation

	India						Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Theil Index	0.576**	0.543**	0.380**	0.235**	0.418**	0.340**	0.221	0.240	0.237
	(0.050)	(0.060)	(0.069)	(0.061)	(0.051)	(0.057)	(0.143)	(0.184)	(0.145)
Constant	0.055**		0.061**		0.078**		0.200**	0.194**	0.200**
	(0.005)		(0.006)		(0.006)		(0.026)	(0.031)	(0.023)
Convergence coefficient	-0.061***	-0.065***	-0.089***	-0.109***	-0.083***	-0.094***	-0.111***	-0.109***	-0.109***
	(0.007)	(0.009)	(0.010)	(0.009)	(0.007)	(0.008)	(0.020)	(0.026)	(0.021)
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.280	0.342	0.108	0.217	0.131	0.226	0.072	0.073	0.057
State Fixed effect	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is Theil index in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial Theil index refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is ordinary least squares. In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.9: Absolute Gini Convergence: Ordinary Least Squares Estimation

	India						Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Gini coefficient	0.573**	0.544**	0.414**	0.294**	0.387**	0.321**	0.190	0.202	0.201
	(0.037)	(0.045)	(0.043)	(0.046)	(0.043)	(0.049)	(0.104)	(0.132)	(0.107)
Constant	0.112**		0.134**		0.168**		0.294**	0.286**	0.299**
	(0.009)		(0.009)		(0.012)		(0.034)	(0.042)	(0.033)
Convergence coefficient	-0.061***	-0.065***	-0.084***	-0.101***	-0.088***	-0.097***	-0.116***	-0.114***	-0.114***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.015)	(0.019)	(0.015)
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.354	0.402	0.186	0.287	0.140	0.221	0.098	0.092	0.083
State Fixed effect	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is Gini coefficient in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial Gini coefficient refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is ordinary least squares. In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.10: Proportionate MLD Convergence

	India						Punjab-Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial MLD (logarithmic)	0.621**	0.621**	0.541**	0.488**	0.455**	0.405**	0.202*	0.214*	0.211*
	(0.036)	(0.046)	(0.046)	(0.068)	(0.052)	(0.062)	(0.087)	(0.097)	(0.103)
Constant	-0.833**		-1.125**		-1.163**		-1.246**	-1.251**	-1.183**
	(0.087)		(0.124)		(0.115)		(0.160)	(0.180)	(0.195)
Convergence coefficient	-0.054***	-0.054***	-0.066***	-0.073***	-0.078***	-0.085***	-0.114***	-0.112***	-0.113***
	(0.008)	(0.008)	(0.009)	(0.010)	(0.011)	(0.012)	(0.012)	(0.014)	(0.015)
Reliability of MLD	0.86	0.86	0.74	0.74	0.78	0.78	0.97	0.96	0.93
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.418	0.464	0.280	0.347	0.171	0.239	0.147	0.136	0.124
State fixed effects	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is logarithmic MLD in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial MLD (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial MLD (see section 3.3.2). In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.11: Proportionate CoVar. Convergence

	India						Punjab-Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial CoVar. (logarithmic)	0.584**	0.559**	0.504**	0.404**	0.459**	0.389**	0.170	0.189	0.195
	(0.041)	(0.052)	(0.050)	(0.071)	(0.054)	(0.063)	(0.112)	(0.124)	(0.120)
Constant	-0.786**		-1.080**		-1.033**		-0.788**	-0.764**	-0.802**
	(0.086)		(0.119)		(0.109)		(0.197)	(0.220)	(0.213)
Convergence coefficient	-0.059***	-0.063***	-0.071***	-0.085***	-0.077***	-0.087***	-0.119***	-0.116***	-0.115***
	(0.006)	(0.007)	(0.007)	(0.010)	(0.008)	(0.009)	(0.016)	(0.018)	(0.017)
Reliability of CoVar.	0.86	0.86	0.77	0.77	0.81	0.81	0.96	0.95	0.89
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.334	0.398	0.221	0.296	0.158	0.237	0.070	0.071	0.085
State fixed effects	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is logarithmic coefficient of variation in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial coefficient of variation (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial MLD (see section 3.3.2). In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.12: Absolute MLD Convergence

	India						Punjab-Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial MLD	0.689**	0.691**	0.527**	0.401**	0.505**	0.444**	0.209	0.218	0.244
	(0.046)	(0.053)	(0.060)	(0.079)	(0.060)	(0.069)	(0.103)	(0.110)	(0.147)
Constant	0.038**		0.043**		0.064**		0.167**	0.160**	0.172**
	(0.005)		(0.005)		(0.008)		(0.019)	(0.020)	(0.026)
Convergence coefficient	-0.044***	-0.044***	-0.068***	-0.086***	-0.071***	-0.079***	-0.113	-0.112	-0.108
	(0.006)	(0.006)	(0.010)	(0.012)	(0.010)	(0.011)	(0.015)	(0.016)	(0.021)
Reliability of MLD	0.86	0.86	0.74	0.74	0.78	0.78	0.97	0.96	0.93
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.358	0.406	0.183	0.270	0.160	0.236	0.117	0.112	0.084
State fixed effects	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is MLD in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial MLD refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial MLD (see section 3.3.2). In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.13: Absolute CoVar. Convergence

	India						Punjab-Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial CoVar.	0.649**	0.617**	0.482**	0.288**	0.544**	0.442**	0.231	0.264	0.282
	(0.056)	(0.064)	(0.082)	(0.102)	(0.067)	(0.075)	(0.223)	(0.237)	(0.255)
Constant	0.062**		0.068**		0.077**		0.306**	0.298**	0.280**
	(0.009)		(0.010)		(0.010)		(0.046)	(0.048)	(0.054)
Convergence coefficient	-0.050***	-0.055***	-0.074***	-0.102***	-0.065***	-0.080***	-0.110***	-0.105***	-0.103***
	(0.008)	(0.009)	(0.012)	(0.015)	(0.010)	(0.011)	(0.032)	(0.034)	(0.036)
Reliability of CoVar.	0.86	0.86	0.77	0.77	0.81	0.81	0.96	0.95	0.89
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.248	0.326	0.087	0.176	0.147	0.247	0.033	0.039	0.041
State fixed effects	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is coefficient of variation in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial coefficient of variation refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is consistent adjusted least squares. Reliability is the reliability coefficient of initial MLD (see section 3.3.2). In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.14: Proportionate MLD Convergence: Ordinary Least Squares Estimation

	India						Punjab-Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial MLD (logarithmic)	0.534**	0.494**	0.400**	0.295**	0.355**	0.292**	0.197*	0.207	0.196*
	(0.032)	(0.039)	(0.035)	(0.041)	(0.042)	(0.046)	(0.086)	(0.105)	(0.089)
Constant	-1.040**		-1.497**		-1.381**		-1.255**	-1.264**	-1.211**
	(0.078)		(0.094)		(0.092)		(0.155)	(0.192)	(0.173)
Convergence coefficient	-0.067***	-0.072***	-0.086***	-0.101***	-0.092***	-0.101***	-0.115***	-0.113***	-0.115***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.012)	(0.015)	(0.013)
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.359	0.410	0.207	0.299	0.133	0.212	0.143	0.132	0.115
State fixed effects	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is logarithmic MLD in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial MLD (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is ordinary least squares. In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.15: Proportionate CoVar. Convergence: Ordinary Least Squares Estimation

	India						Punjab-Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial CoVar. (logarithmic)	0.502**	0.444**	0.388**	0.261**	0.372**	0.294**	0.164	0.179	0.172
	(0.036)	(0.045)	(0.040)	(0.046)	(0.043)	(0.048)	(0.103)	(0.126)	(0.094)
Constant	-0.954**		-1.354**		-1.207**		-0.798**	-0.781**	-0.840**
	(0.077)		(0.099)		(0.089)		(0.181)	(0.223)	(0.177)
Convergence coefficient	-0.071***	-0.079***	-0.087***	-0.106***	-0.090***	-0.101***	-0.119***	-0.117***	-0.118***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.015)	(0.018)	(0.013)
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.287	0.358	0.170	0.268	0.128	0.217	0.067	0.067	0.075
State fixed effects	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is logarithmic coefficient of variation in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial coefficient of variation (logarithmic) refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is ordinary least squares. In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.16: Absolute MLD Convergence: Ordinary Least Squares Estimation

	India						Punjab-Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial MLD	0.593**	0.565**	0.390**	0.256**	0.394**	0.324**	0.203	0.211	0.226
	(0.048)	(0.056)	(0.067)	(0.058)	(0.050)	(0.057)	(0.101)	(0.133)	(0.135)
Constant	0.048**		0.054**		0.077**		0.168**	0.161**	0.175**
	(0.005)		(0.005)		(0.006)		(0.019)	(0.023)	(0.021)
Convergence coefficient	-0.058***	-0.062***	-0.087***	-0.106***	-0.087***	-0.097***	-0.114***	-0.113***	-0.111***
	(0.007)	(0.008)	(0.010)	(0.008)	(0.007)	(0.008)	(0.014)	(0.019)	(0.019)
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.308	0.359	0.135	0.246	0.125	0.211	0.113	0.108	0.078
State fixed effects	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is MLD in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial MLD refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is ordinary least squares. In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Table 3.17: Absolute CoVar. Convergence: Ordinary Least Squares Estimation

	India						Punjab-Pakistan		
	Overall		Rural		Urban		Overall	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial CoVar.	0.558**	0.505**	0.371**	0.199**	0.441**	0.340**	0.223	0.250	0.249
	(0.060)	(0.072)	(0.086)	(0.075)	(0.061)	(0.064)	(0.209)	(0.253)	(0.174)
Constant	0.075**		0.080**		0.093**		0.307**	0.301**	0.286**
	(0.008)		(0.010)		(0.009)		(0.044)	(0.051)	(0.032)
Convergence coefficient	-0.063***	-0.071***	-0.090***	-0.114***	-0.080***	-0.094***	-0.111***	-0.107***	-0.107***
	(0.009)	(0.010)	(0.012)	(0.011)	(0.009)	(0.009)	(0.030)	(0.036)	(0.025)
Observations	478	478	474	474	477	477	34	34	34
R-squared	0.213	0.296	0.067	0.169	0.119	0.229	0.032	0.037	0.037
State fixed effects	No	Yes	No	Yes	No	Yes			

Notes: The dependent variable is coefficient of variation in 2011-12 (India) and 2010-11 (Punjab-Pakistan). The independent variable initial coefficient of variation refers to 2004-05 for India and 2003-04 for Punjab-Pakistan. The convergence coefficient is obtained from the point estimate in the first row by $1+\beta$. The estimation method is ordinary least squares. In all columns, an observation is a district. I add the state fixed effects in columns 2, 4, and 6. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 percent level.

Chapter 4

School Grants and Education Outcomes: The Impacts of a Non-Salary Budget Reform in Punjab Pakistan

**Joint work with Min Xie*

Abstract Whether increasing school funding is effective in improving education quantity and quality is a critical question for the education policymakers. In this essay, we analyze the impacts of a decentralized school grant program in Punjab-Pakistan, the "Non-salary Budget (NSB)" reform. Under this reform, each public school received about ten times the amount of the grant from government which they had received prior to the reform. To identify the effects of the reform, we explore the spatial and temporal variation of the policy rollout. We find that the reform has significantly improved the schools' infrastructure conditions. However, we do not find any discernible effects on student enrollment, attendance rate or test score in the short to medium run.

4.1 Introduction

Education has long been viewed as an important determinant of economic well-being. From the theoretical perspective, education promotes economic growth by improving human capital, increasing the innovative capacity of the economy and facilitating diffusion of knowledge that is needed to implement innovative technologies (Hanushek and Woessmann, 2010). The empirical literature has also established a positive correlation between better education (quantity and quality) and better socioeconomic outcomes, e.g., health (Strauss and Thomas 1995, Schultz 1997, Schultz 2002). Sen (2000) has regarded education itself as an intrinsic good. Development policymakers also show their interest in education, and they know how crucial education is for the process of economic development. For example, the United Nation's "Sustainable Development Goals" call for quality education for all by 2030.[1]

These arguments have provided justifications for widespread education interventions implemented in the hope of improving education quantity (i.e., student enrollment and attendance) and quality (i.e., learning outcomes such as test score). Two broad categories of interventions based on human capital and physical input respectively have been put to the test in the literature. On the one hand, human capital-based intervention aims to improve human capital in the education sector through pedagogical innovation (Duflo et al. 2011, Chen et al. 2017, Naik et al. 2020), teachers' accountability (Duflo et al. 2011, Duflo et al. 2012, Muralidharan and Sundararaman 2011, Mbiti 2016), students' tracking (Duflo et al. 2011) and school governance (Banerjee et al. 2010, Pradhan and De Ree 2014). This method has generally yielded positive effects on students' test scores and attendance. On the other hand, the physical input-based method seeks to improve education quantity and quality by easing the constraints on physical resources. These resources could be textbooks (Glewwe et al. 2009, Frölich and Michaelowa 2011), flipcharts (Glewwe et al. 2004), radio (Pridmore and Jere, 2011), computer assistance (Banerjee et al. 2007, Cristia et al. 2017, Kremer et al. 2013), libraries (Borkum et al. 2012), school buildings (Newman et al. 2002), sanitation (Adukia 2017), etc. However, a consensus has emerged from these studies that investing in physical inputs does not have

[1]The United Nations Sustainable Development Goal 4 aims at "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all". For more details on targets and facts see: https://www.un.org/sustainabledevelopment/education/.

any discernible impact.[2]

A specific constraint that may limit the effectiveness of physical inputs on improving education outcomes is the centralized provision of these inputs. Four issues arise from the centralized provision of inputs. First, there is an often mismatch between the demand at the local level and the provision determined at the national level regarding the school resources. Decision-makers at the local level have a better understanding of the schools' needs than those at the national level. Therefore, they are in a better position to identify schools' deficiencies and to use the resources efficiently (Carneiro et al. 2020, Hanushek and Woessmann 2011). For example, in Kenya, Glewwe et al. (2009) do not find any effects of the textbooks on students' test scores because the textbooks provided to the schools are too complicated for both students and teachers. Second, centralized provision is more prone to delivery failure. The information asymmetry between the central decision-maker and the local implementation administrator appears to be more severe than in a decentralized scenario. In Sierra Leone, Sabarwal et al. (2014) show that the centralized provision of textbooks does not have any impact on students' test scores. The reason for this is that most of the books have been kept in the schools' storage room, and so fail to reach the students. Third, political pressure to initiate visible education policies may also lead education systems to invest in less effective inputs (Mbiti, 2016). For example, a politician may choose to give each classroom a computer not because it is an effective way to improve education outcomes, but instead due to the fact that it is more visible to show the existence of computers as an achievement to voters. Finally, complementarities among multiple inputs may limit the effectiveness of a single input (Mbiti et al., 2019). For example, giving a tablet to each school without training the teachers to incorporate the tablet into their teaching would not be likely to affect the students' learning.

One potential way to avoid these issues and improve efficiency is to provide unconditional cash grants and devolve the financial decision-making to the school councils, i.e., decentralized school grants.[3] This seeks to increase efficiency by mak-

[2]Multiple review papers show that pedagogical interventions (Kremer et al. 2013, Conn 2014), computer uses and technology (McEwan 2015), and learning material (Krishnaratne et al. 2013) are among the most effective ways to improve the students' learning outcomes. Above-mentioned reviews generally believe that input-based policies are mostly unsuccessful in increasing students' achievements.

[3]The school council is a school-based management committee that consists of teachers, parents

ing financial decisions more transparent to communities, reducing corruption and incentivising localised investment in high quality teachers and materials (Carr-Hill et al., 2018). However, this is debated since decentralized school grant does not necessarily bring efficiency gains because the school councils do not necessarily possess sufficient capacity in making complex decisions at the local level. Although the allocation of school grants is associated most strongly with the devolution of financial decision-making (e.g., decisions about how resources should be allocated within a school), depending on the nature of the needs identified at school level, the allocation of school grants might also touch on managerial decision-making (e.g., the recruitment and monitoring of teacher performance) or educational decision-making (e.g., decisions related to improving the articulation of a school's curriculum) (Carr-Hill et al., 2018). Therefore, when implemented in contexts with a lack of decision-making capacity, decentralized school grants may result in the inefficient and ineffective use of resources (Hanushek and Woessmann, 2011).

In this study, we address two questions. First, does providing decentralized school grants improve the education quantity and quality? Second, does this decentralized grant have any impact on human capital (measured by teacher's attendance rate) and school's physical infrastructure? In particular, we study the impacts of the "non-salary budget (NSB)" reform in Punjab-Pakistan. Each public school in Punjab provides education for 1st to 5th graders. Before NSB reform, public schools in Punjab received Rs. 20,000 (approximately 200 USD in 2013) per annum, and an annual addition of Rs. 20,000 if the schools offer education beyond the 5th grade.[4] This fixed grant has proven to be extremely insufficient even for the basic school maintenance. A rough estimate of the annual recurrent expenditure of a school is Rs. 70,000.[5] The underfunding for the non-salary expenditure has persistently hindered public schools' ability to attract and retain students.

Against this backdrop, the Punjab government implemented the NSB reform in 2013. The NSB reform alters the funding allocation rule from a fixed to a need-

and notable local members. Providing decentralized school grants has emerged as a part of relatively recent practices for educational decentralization. These practices focus on devolving the decision-making concerning the curricula, finance, management and teachers (Bruns et al. 2011, Slater 2013).

[4] Primary: grade 1-5. Middle: grade 6-8, High: grade 9-10 and Secondary High: grade 11-12.

[5] This estimation is based on informal interviews with several school headteachers and members of teacher unions across Punjab.

based rule. The need-based formula includes indicators such as school level, student enrollment, furniture deficiency and building condition. Under this need-based rule, the average annual non-salary budget per school amounts to Rs. 220,000, which is about ten times the amount that was received under the erstwhile fixed allocation rule. The NSB reform was rolled out in three phases to cover the whole province. In 2013, nine districts were selected for phase one. In 2014, additional nine districts were added in phase two. Since 2015, the NSB reform was extended to the whole of the Punjab province. The reform's staggered roll-out schedule has created temporal and geographical variations in policy treatment which we exploit to estimate the reform's impacts.

We combine data from various sources. First, we collect schools' financial accounts and infrastructure conditions from the "Annual School Census (ASC)", administered by the school and education department of Punjab (SED). The ASC is also used by the officials to calculate the school's NSB entitlements under the new rule. Second, we collect the test scores of grade five students, the terminal grade of primary school, from the Punjab Examination Commission (PEC), which is the organization for conducting standardized exams for students from the Punjab province. Third, we use English reading and mathematical ability scores of children of age 5 to 16 from the "Annual Status of Education Report Pakistan (ASER)" as an alternative measure of learning outcomes. Fourth, we measure the enrollment rate by the share of children of age between 5 and 16 who are currently enrolled in a school by using the "Multiple Indicator Cluster Survey Punjab (MICS-Punjab)", a UNICEF-administered household survey. Finally, we obtain students' and teachers' attendance from the Punjab Monitoring and Implementation Unit (PMIU), a government department that administrates monthly attendance surveys at the school level.

We report four sets of results. First, regarding the schools' financial accounts, the NSB reform has significantly increased the schools' annual income and expenditure by Rs. 180,000 and Rs. 135,000, respectively. Second, we find that the reform has significantly improved the conditions of school infrastructures by 0.045 standard deviations. This effect is driven by improvements in the existing infrastructures, e.g., the fraction of functional toilets, complete boundary walls and the safe school's building. In terms of human capital, we find that teachers' attendance rate has increased slightly by 0.9 percentage points, a value that is only 1% of the average at the baseline. Third, we do not find any effect on education quantity as measured by students' attendance rate and the enrollment rate among children of age 5 to 16. Fourth, in terms of education quality, we do not find any impacts on students' numeracy and literacy test scores and ability scores.

This paper contributes to the debate about the effectiveness of decentralized school grants for improving education outcomes in developing countries. The empirical evidence is still limited and mostly based on small scale RCTs. Nevertheless, this limited empirical literature has suggested that decentralized school grants' impacts on education outcomes are only moderate and its effectiveness is highly contextual. Some lessons can be drawn from these studies. These include the following.

First, local decision-makers should be supported to build sufficient capacity in understanding school-based management and making informed spending decisions that are likely to improve education outcomes. Blimpo et al. (2015) conduct an RCT in the Gambia to study the complementarity between school grant and training for the school management committee. They find a strong complementarity between the two treatments. Providing schools with grants alone does not have any impact. Studying a school grant program that encourages parental participation in school management in Nigeria, Beasley and Huillery (2017) show that, although the program is capable of improving parental participation, it fails to deliver an impact on students' educational outcomes because the parents lack the capacity to make effective decisions in school management.

Second, the effectiveness may be hampered by behavioral responses on the part of stakeholders. Das et al. (2013) study the school block grant programs in India and Zambia using experimental designs and find that the school grants improve the students' test scores only if the grants are unanticipated to the parents. If anticipated, the grants crowd out parental investment in their children's education. Competition from the education market also affects schools' decisions. Andrabi et al. (2020) use RCT to study how market competition affects the effectiveness of school grants among private schools in Punjab Pakistan. They find that, while villages with all schools who were given the block grant (i.e., high saturated villages) see an improvement in students' test scores, villages with only one school given the grant (i.e., low saturated villages) see an improvement in enrollment. They explain that, in order to increase profit, private schools in low saturated villages act as monopolists (on the residual demand from the untreated schools) and bring in additional students by increasing infrastructures investments, while schools in high saturated villages trigger a price war if they do the same because of their lack of monopolistic power. Therefore, schools in the high saturated village resort to improving test scores (in order to raise tuition and profit).

Third, spending on improving teaching human capital seems to be promising. Carneiro et al. (2020) show that a school grant program in Senegal improves the test scores of the second graders, especially in schools that spent on human resources training, rather than on the acquisition of school materials (e.g., textbooks). Consistent with this finding, the impacts of the Nigeria program as studied by Beasley and Huillery (2017) is mainly captured by schools where teachers have benefited from the spending.

Our study's contribution to this strand of the existing literature is three-fold. First, we add evidence to the limited and recent empirical literature on the effectiveness of decentralized school grants in improving education outcomes in the context of Punjab-Pakistan's "NSB" reform, which, to the best of our knowledge, has not been evaluated until now. Second, rather than adopting the context of an experimental setting, we study a real large-scale policy, which is more likely to capture the real-world effect. Third, this study sheds light on Punjab-Pakistan's progress on achieving the "Sustainable Development Goal (SDG)" which has set multiple education-related targets: equal access, gender equity, equitable quality education, conducive learning environments and adequacy of trained teachers, all of which are related to our results.

A major limitation of this paper is the short-run nature of the findings because our identification strategy relies on the variation in treatment timing across three reform phases which differ only by one to two years. However, a long-run analysis is impossible as the policy has covered the whole province within a time span of two years. Therefore, it is possible that different results would have emerged if the reform had been allowed a longer duration of each phase, especially for education quality which takes a longer time to improve than does school infrastructure. However, the results presented here are still useful. The richness of the data on school inputs gives some insights into the decisions of the spending and their effectiveness.

The rest of the study is organized as follows. Section 4.2 introduces the institutional background and the NSB reform. Section 4.3 describes the data. Section 4.4 discusses the identification strategy. Section 4.5 presents the main results. In section 4.6, we conduct some robustness checks. Finally, section 4.7 concludes.

4.2 Institutional Background and the Non-salary Budget Reform

Insufficient funding for education has been a critical problem for achieving the goal of providing quality education throughout Pakistan as a whole. Twenty-five million children are still out of school in Pakistan, of which nine million are in Punjab, Pakistan's largest province (Alif Ailaan, 2014a). Education spending in Pakistan is stagnant at 2 percent of GDP in the past two decades.[6] This low level of education funding is falling short of the international benchmark, which is currently set at 4%. More seriously, the share of the non-salary budget in the total education budget is only 12%. In Punjab, this share stands at a mere 3%, while the salary and developmental education budget make up 86% and 11%, respectively (I-SAPS, 2015).

Public schools' non-salary expenditure is funded by two sources, provincial government and parents. Prior to the NSB reform, an average public school received a fixed grant of Rs. 20,000 or 40,000 per annum from government depending on the school level, and approximately Rs. 24,000 per annum from parental contribution (Rs. 20 per student per month). This funding for the non-salary expenditure is extremely insufficient for any school to maintain its facilities. A rough estimate of annual recurrent expenditure is Rs. 70,000 (excluding building maintenance). According to our interviews with the headmasters and teachers of the public schools, some schools manage to cover the deficit in NSB by selling trees from the school-

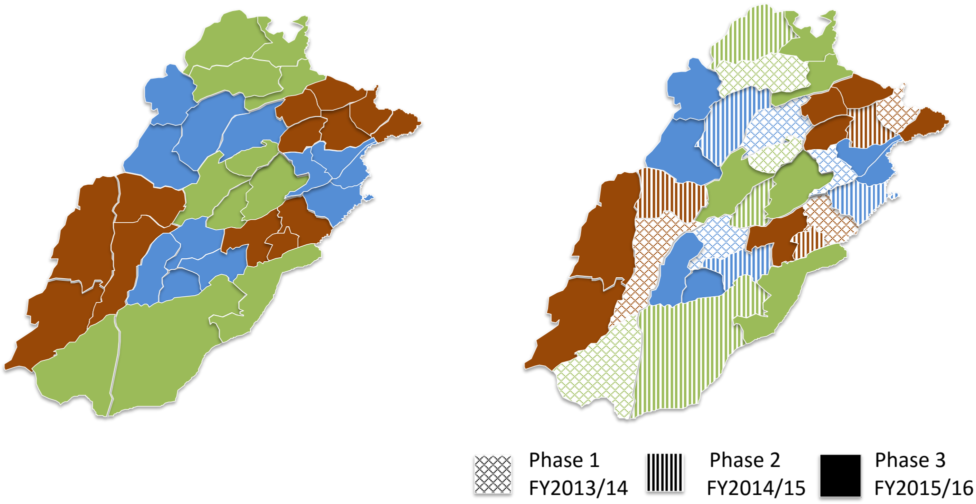
[6]This figure is extracted from various waves of the Pakistan Economic Survey by the Ministry of Finance of Pakistan. See: http://www.finance.gov.pk/survey_archieve.html

yard and asking for donations in cash or in kind from local villagers. In some cases, the headmasters or teachers use their personal relations to approach the member of the Provincial and National assembly to seek discretional funds for schools. Occasionally, teachers advance the expenditure from their own pockets, and reimburse themselves from the next round of funding. There are even cases where schools impose fines on the students, if they are late from school or for not wearing school uniform.

Against this backdrop, the school education department, with the support of the World Bank, had designed and implemented a need-based non-salary expenditure funding policy, i.e., the non-salary budget reform, starting in the financial year (FY) 2013/14. Under this reform, the annual amount of NSB is no longer fixed but based on a set of school-need indicators, which include school level, student enrollment, furniture deficiency and infrastructure condition. An average public school receives an annual grant of Rs. 220,000 which is paid in 4 installments. School councils are made accountable and responsible for planning, managing and administrating the NSB grant. The grant can be used to cover a wide array of non-salary expenditures, e.g., construction, stationery, furniture, teaching materials, provision of electricity and water and sports goods.

The reform was rolled out in three phases and was planned to cover the whole province in three years. Figure 4.1 visualizes the geographical coverage of this staggered roll-out schedule. The province of Punjab is divided into nine divisions, with each division consisting of 3 to 6 districts. In total, there are 36 districts in Punjab. The selection of districts into different phases is stratified at the division level. In the first phase in FY2013/14, one district per division was selected (i.e., nine districts in total). In the second phase in FY2014/15, an additional district per division was selected (i.e., 18 districts in treatment including phase one districts). Finally, in the third phase in FY2015/16, the program was rolled out to all 36 districts.[7]

[7]Nine districts of phase 1: Chakwal, Chiniot, Khanewal, Muzaffargarh, Nankana Sahib, Okara, Rahim Yar Khan, Sargodha and Sialkot. Additional nine districts of phase 2: Attock, Bahawalpur, Gujranwala, Kasur, Khushab, Layyah, Pakpattan, Toba Tek Singh and Vehari.



Note: The left panel shows the map of Punjab-Pakistan which consists of 36 districts whose boundaries are drawn in white. These 36 districts make up nine divisions that are separated by colors. The right panel shows the "NSB" reform's coverage across districts and phases.

Figure 4.1: Non-salary Budget Reform's Rollout

The selection of districts into different phases was determined by the reform committee that was led by three members. While the exact selection rules for pilot districts were not documented, the committee disclosed to us that the rules were not systematic and the selection was rather based on general impressions of the districts' ability of information updating, as the committee relied on this ability to monitor the reform's implementation and progress. The information was delivered by the districts' education officers (EO). A typical EO is made responsible for several public schools. Their responsibilities include conducting school surveys, maintaining the administrative records of schools, implementing education initiatives in the field and ensuring delivery of quality education. We show the robustness of our main results by the addition of a proxy for the EO's effort in the section of robustness check.

4.3 Data

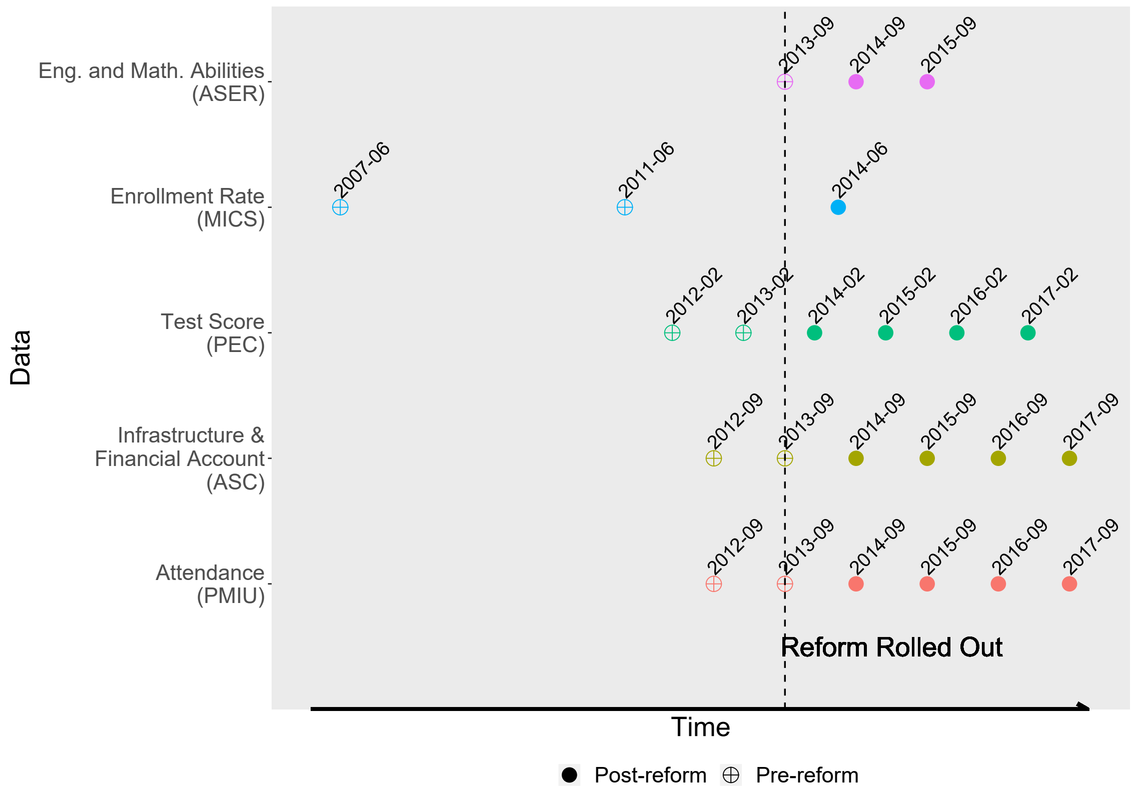
We use both administrative and household survey data for our analysis. We compile a school-year panel using administrative data from three sources. First, we collect the information on school infrastructure, facilities and financial accounts from the "Annual School Census (ASC)", which is conducted in September annually by the

School and Education Department (SED). The ASC is also used by the reform committee to calculate the schools' NSB entitlement. Secondly, we obtain the teachers' and students' attendance rate from the Program Monitoring and Implementation Unit (PMIU). In order to collect this information, PMIU hires approximately 900 Monitoring and Evaluation Assistants (MEAs) to administer the monthly survey in all public schools in Punjab. The MEAs are assigned to school clusters in such a way that they are able to visit at least 4 schools per day. The MEAs' assignment is rotated every month, which prevents MEAs from forming personal relationships with the school staff of a particular area. We aggregate the monthly data to annual level. Lastly, we obtain the standardized test scores of the fifth-graders who need to pass the test in order to advance to middle school. The test scores are obtained from the Punjab Examination Commission (PEC), which is SED's autonomous body that administers the standardized exam. The exam is held annually in February and consists of five subjects, namely Urdu, English, Islamic study, Math and Science. Each subject requires 40 points (out of 100 points) to pass. We categorize these five subjects into two categories: numeracy and literacy, where numeracy consists of Math and Science, and literacy, which contains the other three subjects. We calculate the category-wise average score and standardize this average score to a z-score, year by year.

In addition, we compile a district-year panel from two independent household surveys, namely the Multiple Indicator Cluster Survey (MICS-Punjab) and the Annual Status of Education Report (ASER-Pakistan). The MICS-Punjab is part of the global MICS programme that was developed by UNICEF in the 1990s as an international multi-purpose household survey programme to support countries in collecting internationally comparable data on a wide range of indicators on the situation of children and women. MICS-Punjab is not available on an annual basis and we only use the three most recent survey waves (i.e., 2007, 2011 and 2014), which are cross-sectional household surveys. However, all survey waves provide a district identifier for each sample household that allows us to build a district-year panel. For each household, MICS-Punjab records basic information of all household members, including age and whether the member is currently enrolled in a school. Following UNICEF's criteria, we calculate the enrollment rate of a district as the share of children of age between 5 and 16 that are currently enrolled in a school. To measure the children's learning outcomes from another perspective, we use the ASER-Pakistan children surveys of the wave of 2013, 2014 and 2015. ASER-Pakistan is conducted in September when the new school year starts. It aims to provide reliable estimates on the schooling status of children aged between 5 and 16 years who live in Pakistan. Similar to MICS-Punjab, ASER-Pakistan is a cross-sectional household survey with district identifiers that allow us to compile the information for a district-panel. ASER-Pakistan grades children's English and mathematical abilities by five levels.[8] For our analysis, we rescale the scores as follows. "English Ability" is graded as 1 if the child can't read, 2 if he or she can recognize letters/words or 3 if he or she can read sentences. Similarly, a child's "Mathematical Ability" is graded as 1 if she has zero knowledge, 2 if can recognize numbers or 3 if can perform mathematical operations. Under this scale, the higher the score, the higher the abilities to read English or perform mathematics.

The data structure is presented in Figure 4.2. Our school-year panel consists of six years of data on an annual frequency. The reform started to roll out in September 2013. However, according to a third-party evaluation report on the reform implementation, the grants did not arrive at the schools until the last quarter of 2013 due to the systematic technical issues with the provincial and district governments (Cambridge Education, 2014). Therefore, we regard the first two years as pre-reform. Our district-year panel is relatively shorter with three years of data from ASER and MICS. The timing of the reform roll-out determines that we have two years of pre-reform data for enrollment rate and one for children's English reading and mathematical abilities.

[8] English: "Can't read", "Recognize capital letters", "Recognize small letters", "Can read words" and "Can read sentences". Mathematics: "Zero knowledge", "Recognize numbers 1-9", "Recognize 10-99", "Can perform subtraction" and "Can perform division".



Note: “English and Math Abilities" and “Enrollment Rate" are district-level variables aggregated from household surveys of ASER and MICS. “Test Score", “Infrastructures & Financial Account" and “Attendance" are school-level variables collected from administrative data.

Figure 4.2: Data Structure

The summary statistics of the pre-reform data is presented in Table 4.1. There are 48,310 public schools in our sample, of which 47% are boys’ schools. All public schools offer education from grade 1 to 5, which is the primary-level education. Among all public schools, 16% offer additional grade 6 to 8, i.e. middle-level education. Furthermore, 13% offer teaching at grade 9 to 10, i.e. high-level. In comparison, only 1% public schools offer additional grade 11 to 12 teaching, which is the secondary-high-level education in Punjab-Pakistan. Regarding the financial accounts, an average public school receives approximately Rs. 32,000 from government and spends Rs. 40,000 in total per year. It should be noted that the public schools also receive funds from parental contributions and NGOs whose records are not available for most of the schools and are therefore not included in our analysis. Absence of basic facilities such as drinking water, electricity, main gate or toilet is rare. However, the conditions of the school buildings and boundary wall are relatively poor, with only 59% of the schools reporting their building conditions to be safe and 87% reporting their boundary walls to be complete. To measure the overall status of the infrastructure of a school, we calculate an infrastructures index, which takes the simple average of the z-scores of all the aforementioned infrastructures variables. It then intuitively measures how different a school's infrastructures status is from the average status of all schools. Similarly, we calculate a sports facilities index to capture the overall sports supplies sufficiency in a school. These supplies include cricket, football, hockey, badminton and table tennis. Regarding attendance, students' attendance rate in different levels of education are quite high. 85% of the registered students in grade 1 to 5 were present during a MEA's visit. This value is 88%, 87% and 84% for grade 6-8, 9-10 and 11-12, respectively. Teachers' attendance rate in an average public school stands at around 87%. In terms of the scores of the grade-5 test, which a student needs to pass to advance to the middle-level education (i.e., grade 6-8), the average raw score of all numeracy subjects is 41 points, which is on the verge of passing. Raw literacy score appears to be higher, reaching 50 points. In our analysis, we normalize the scores using the same method as was used in calculating the infrastructures index. Score normalization is a common practice in assessing the impacts on test scores. The normalized score allows for comparison across samples, as well as with the results from other studies (Glewwe and Muralidharan, 2016).

Table 4.1: Summary Statistics: Pre-reform

	Mean	Std.dev	Min	Max	N
School Cross-sectional					
Male	0.470	0.500	0	1	48,310
Primary	0.690	0.460	0	1	48,310
Provide education for:					
Grade 6-8 (Middle)	0.160	0.370	0	1	48,310
Grade 9-10 (High)	0.130	0.330	0	1	48,310
Grade 11-12 (Secondary High)	0.010	0.110	0	1	48,310
School Panel					
School grant received (10,000 Rs.)	3.250	7.490	0	218	82,550
Expenses (10,000 Rs.)	4.130	8.190	0	235	82,550
Building condition is safe	0.590	0.490	0	1	82,550
Boudary wall is complete	0.870	0.340	0	1	75,097
Drink water exists	0.980	0.150	0	1	82,550
Electricity exists	0.820	0.380	0	1	82,550
Main gate exists	0.920	0.280	0	1	82,550
Toilet exists	0.998	0.048	0	1	82,550
Share of functional toilets	0.950	0.180	0	1	82,550
Infrastructures index	0.035	0.390	-3.320	0.450	82,550
Sports Facilities index	0.003	0.600	-0.320	4.460	82,550
Teacher attendance rate	0.870	0.100	0.060	1	96,574
Student attendance rate					
Grade 1-5	0.850	0.090	0.040	1	91,678
Grade 6-8	0.880	0.070	0.080	1	26,447
Grade 9-10	0.870	0.090	0.020	1	11,993
Grade 11-12	0.840	0.150	0.210	1	1,025
Grade 5 Standardized Test Score					
Numeracy (Raw)	40.949	12.912	0.000	90.638	86,989
Literacy (Raw)	50.044	11.900	0.000	86.167	86,989
Numeracy (Normalized)	0.040	0.990	-3.220	3.800	86,989
Literacy (Normalized)	0.050	0.980	-3.840	3.170	86,989
District Panel					
Math. Ability Score	2.389	0.156	1.978	2.634	36
English Ability Score	2.244	0.162	1.812	2.543	36
Enrollment Rate	0.708	0.121	0.390	0.895	71

Note: Numeracy subjects: Mathematics and Science. Literacy subjects: English, Urdu, Islamic religious study. Infrastructures index is the average of the z-scores of the following variables: Building condition is safe, Boundary wall is complete, Drink water exists, Electricity exists, Main gate exists, Toilet exists and Share of functional toilets. Sports facilities index is the average of the z-scores of five dummy variables for the existence of the following five respective sports facilities, i.e., cricket, football, hockey, badminton and table tennis.

As revealed by the reform committee, the selection into early phases is based on the districts' information update ability, rather than purposefully on the districts' improvement potentials. In order to assure that there is not targeting on the observables, we conduct a balance test using the baseline data (first year of each variable). Specifically, we run the following regression model,

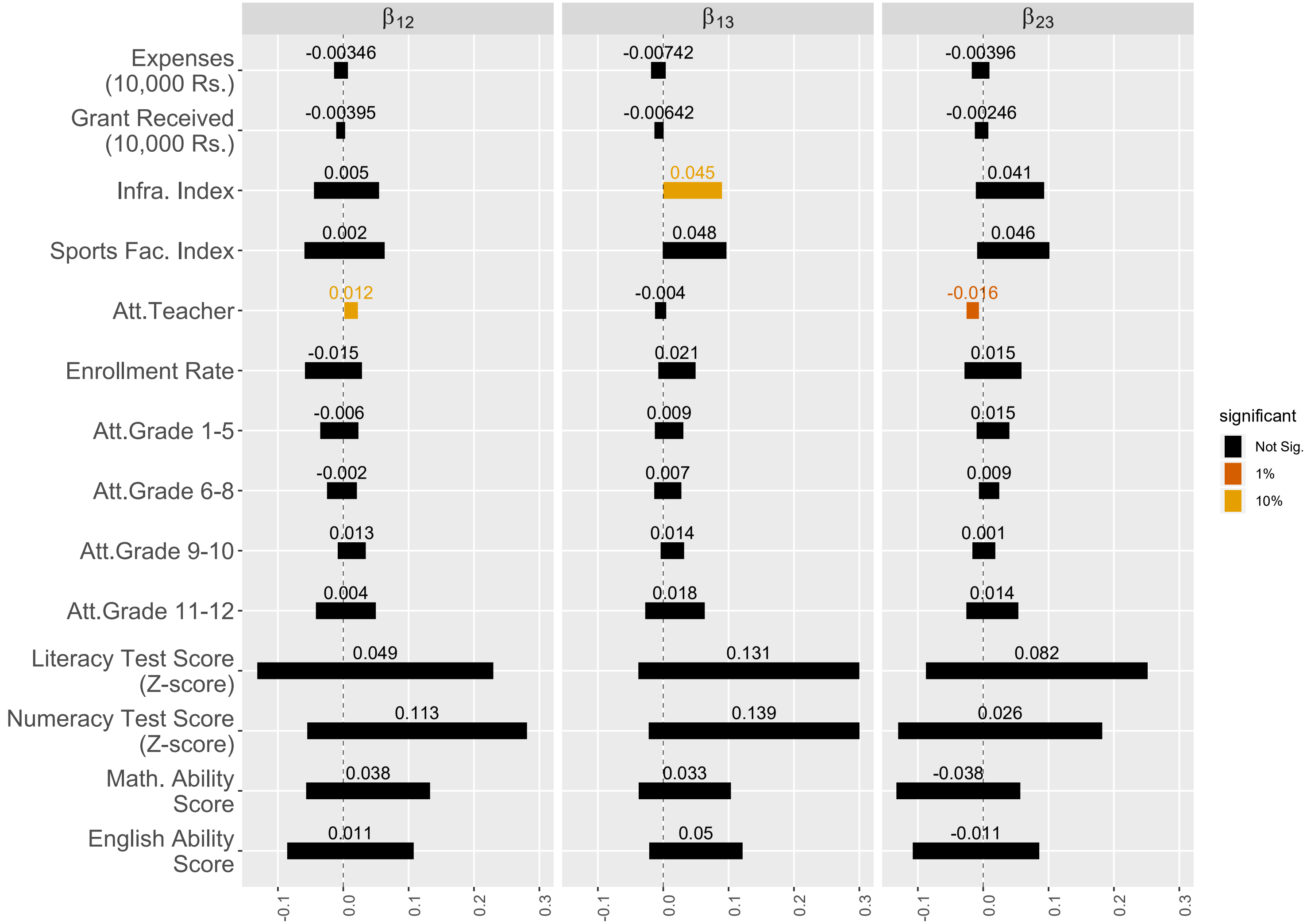
$$\begin{aligned} y_{dr} &= \beta_{13} * PHASE1_d + \beta_{23} * PHASE2_d + \eta_r + u_{dr} \qquad (4.1) \\ \beta_{12} &= \beta_{13} - \beta_{23} \end{aligned}$$

where y_{dr} is the observable in district d and division r at baseline. $PHASE1_d$ and $PHASE2_d$ are respectively the dummy variables for the first and second phase assignments of district d. Since the selection is stratified at the division level, we add the division fixed effects, η_r. Therefore, β_{13} captures the baseline difference in observable of the first, relative to the third, phase districts. Similarly β_{23} is the difference of the second, relative to the third, phase districts. The difference between the first and second phase (with the second phase as reference), β_{12}, is estimated by the difference between β_{13} and β_{23}.

Running model (4.1) on 14 outcome variables, we report the results of this balance test in Figure 4.3. Each bar represents an estimate of β. We plot the point estimates of β_{12}, β_{13} and β_{23} along with their 90% confidence interval in the left, middle and right panel, respectively. There are some statistically significant differences in teacher attendance rate and infrastructures index. Teacher attendance rate in phase 2 appears to be the lowest and phase 3 infrastructures' condition is worse than in phase 1. However, among the 42 point estimates, only 3 show up significant and 2 of them are only at the 10% level. Given the non-experimental setting in this study, we consider the observables are sufficiently balanced at the baseline, i.e., there is no obvious selection on these observables regarding the phase assignment.

4.4 Empirical Strategy

In our analysis, we focus on estimating the average intent-to-treat effect (AITT), i.e., the average effect of becoming subjected to the NSB reform. In doing so, we exploit



Note: Numeracy subjects: Mathematics and Science. Literacy subjects: English, Urdu, Islamic religious study. Infrastructures index is the average of the z-scores of the following variables: Building condition is safe, Boundary wall is complete, Drink water exists, Electricity exists, Main gate exists, Toilet exists and Share of functional toilets. Sports facilities index is the average of the z-scores of five dummy variables for the existence of the following five respective sports facilities, i.e., cricket, football, hockey, badminton and table tennis.

Figure 4.3: Balance Test at the Baseline

the spatial and temporal variations induced by the policy roll-out. Specifically, we use the following econometric specification,

$$y_{sdt} = \beta * TREATED_{dt} + \alpha_s + \gamma_t + u_{sdt} \tag{4.2}$$

where y_{sdt} is the outcome of school s in district d and year t. $TREATED_{dt}$ is the dummy variable for district d entering treatment in year t. α_s and γ_t are school and year fixed effects. β thus captures the average effects of entering the NSB reform. Essentially, this is a double-differences approach with variation in treatment timing. Effectively, β is a weighted average of all possible two-group/two-period double-differences estimator in the data (Goodman-Bacon, 2018). β delivers only the short-run (one to two years) effects of the reform because the treatment timing across the three phases differs only by one (between phase-1 and 2, or phase-2 and 3) to two (between phase-1 and 3) years.

This specification controls for the time-variant factors common to all schools, i.e., year fixed effects, and the school specific time-invariant factors, i.e., school fixed effects. The confounders of $TREATED_{dt}$, if there is any, have to be school-specific time-variant. In our case, the selection of school/district to enter the early phases could bias the estimate of β if the selection criteria are based on the schools'/districts' improvement potential on the outcomes. However, there are two reasons to reassure us that this selection bias is limited. First, the reform committee revealed that the selection was based on the districts' ability of information updating. As the reform has been planned to eventually cover all districts in Punjab, the committee did not have any obvious incentive to purposefully select the better improvers into early phases. Given the capacity constraint, the committee was more concerned about a smooth implementation process. More specifically, a district was selected into early phases if the district had a group of education officers (EOs) who were more responsive to the reform committee. Therefore, the selection bias can be reduced by controlling for the district's EOs' information update ability. We discuss the addition of this control in our robustness section. Second, the balanced outcomes across phases at baseline (Figure 4.3) reassures that the committee did not purposefully select on the districts' improvement potentials, at least on the observables.

The critical assumption in our identification strategy is that the outcomes in different phases would have evolved in parallel had the reform been absent, i.e., "the common trends" assumption. The data structure allows us to conduct a placebo test for the validity of this assumption. We demonstrate the placebo test in detail in the robustness section.

4.5 Results

4.5.1 School's Financial Account

If the policy is expected to have impacts on education outcomes, the grants need to be received and spent by the schools first. We begin by presenting the results on schools' financial accounts. As suggestive evidence, we group the schools by the reform phase assignments and plot the average amount of grant received and spent in the last 12 months by phases against the years in Figure 4.4. As shown in the upper panel of the figure, an average public school received around Rs. 30,000 before the reform. However, the amount of school grants received by the phase-1 schools in the last 12 months has seen a discontinuous increase to Rs. 210,000 in September 2014, exactly 12 months after the phase-1 reform rolled out in September 2013. Similarly, phase-2 and phase-3 schools saw a similar discontinuous increase in 2015 and 2016 respectively, exactly one year after they became subjected to the reform. The three staggered discontinuities in the three phases mimic the staggered roll-out schedule of the reform. We notice that the average amount of the receipt dropped slightly after schools entered the treatment. There are two reasons contributing to this drop. First, as we mentioned, the PMIU recalculated the need-based school grant entitlements on an annual basis. The drop could reflect the decrease in school needs due to the improvement during the previous year. Second, there are delay issues in grant disbursement since 2016 (Khattak 2015, DAWN 2018). Although this delay is not yet fully understood to us at this moment, it has been accounted for by the year fixed effects in model (4.2) because the decreasing trend is common to all phases. Regarding spending, the lower panel also shows a similar staggered pattern, suggesting that the schools responsively increased their expenditure. Overall, this is a strong evidence that the need-based grants have been received and spent by the schools.

Note: The results are calculated using school-year panel data. Schools are grouped into three phases based on the policy phase assignments of the districts where the schools are located. Then for each phase-year, we calculate the average grant received/expenses.

Figure 4.4: School Grant Received from the Government by Phase and Year

To estimate the average policy effect on the schools' financial accounts, we run model (4.2) and the results are presented in Table 4.2. When an average public school becomes subjected to the NSB reform, it receives Rs. 180,000 more from the government, which is 6 times the amounts before the reform (column 1), and spends Rs. 135,000 more, a value that is three times the average before the reform (column 2) .

Table 4.2: Policy Effects on School's Financial Account

	Grant Received (10,000 Rs.)	Expenses (10,000 Rs.)
	(1)	(2)
TREATED	18.18***	13.59***
	(1.85)	(1.35)
Observations	278,779	278,779

Note: The dataset is a school-year panel. Standard errors are clustered on the district level. The analysis covers all 36 districts in Punjab-Pakistan. *p<0.1; **p<0.05; ***p<0.01

4.5.2 School Inputs

Seeing that the schools have increased their spending, we are interested in understanding whether the spending has improved the schools' conditions. The rich data from the ASC provides us with an opportunity to test a large quantity of outcomes. However, it is considered problematic to do so for two reasons. First, we will encounter the issue of multiple hypotheses testing where there is a danger of overinterpreting any single significant result on a specific infrastructure, especially when there are many possible outcomes without a single possible causal pathway (Banerjee et al., 2015a). Second, due to the fungibility of the school grant, heterogeneity in grant uses can make some effects hard to detect (Banerjee et al., 2015b). Therefore we aggregate the infrastructures outcomes into an infrastructures index as a way to capture the effect on overall infrastructures condition and reduce the danger of overinterpreting. The results are presented in Table 4.3. As shown in column (1), the overall infrastructures condition indeed witnessed an economically and statistically significant improvement by 0.045 standard deviations. When looking at the impacts on the components of the infrastructures index, we see an interesting pattern. As shown in table 4.4, we find that the NSB does not avail more facilities, i.e., drinking water, electricity, main gate or toilet (column 1 to 4), but improves the condition of the existing infrastructures (column 5 to 7). Specifically, the share of functional toilets saw an increase of 1.5 percentage points. The building condition of the schools is 7.4 percentage points more likely to be safe, an improvement that is 13% relative to the pre-reform level. The boundary wall is 1.5 percentage points more likely to be complete, an improvement amounts to 1.7% of the average before the reform. Similarly, we aggregate the availabilities of various sports facilities into a sports facilities index whose result is shown in column (2) of table 4.3. We find that policy effect on the overall availablity of sports facilities is nonexistent in that the point estimate is both statistically and economically insignificant.

Of course, there are other items, e.g., textbooks, stationery and teaching materials quantity and quality, on which the schools may have spent the grants. However, we could not include them in our analysis due to the lack of data. Nevertheless, we project the improvement on these items to be limited as the improvement on the existing infrastructures involved construction works that cost a majority of the grant. In fact, Cambridge Education (2014), a review on the expenditures by public schools in Punjab, reports that in the school year of 2013/14, only 2% of the 400 sample schools ever spent the budget on learning and teaching materials. In comparison, 65% of schools reported ever spending the budget on school buildings and other infrastructures. Overall, these results are consistent with Kremer (2003) who points out that providing larger grants to schools in Kenya led school committees to shift spending toward construction from textbooks.

While the reform has sharply increased the school grants for non-salary items, teachers can still indirectly benefit from the non-salary spending, e.g., from the improvement of the classroom condition. Compared to the school infrastructures and facilities, the information on human capital is quite limited to us. The only variable available to us to approximate the human capital quality is the teacher attendance rate. In fact, teacher's absenteeism is a major concern in Punjab's education reform. Punjab has been criticized by its large share of ghost teachers and multi-grade teaching problems. It is necessary to keep teachers in school, before teachers can make efforts to improve teaching. Column (3) of table 4.3 shows that the NSB indeed improves the teacher attendance rate by 0.9 percentage points. However, this magnitude is rather nominal as it makes up only 1% of the average teacher attendance rate before the reform, or one hour per month from another perspective.[9] The reform may also affect teachers' effort on improving their pedagogy, which is in fact a promising way for education outcome improvement (Glewwe and Kremer 2006, Glewwe and Muralidharan 2016). This is especially relevant in the context of

[9] Assuming teachers teach 6 hours per school day and 20 school days per month, an increase of 0.9 percentage points in teacher attendance rate is equal to $0.009*6*20 = 1.08$ hours per month.

Punjab-Pakistan as the education system is characterized by its low effort of teaching (Naviwala, 2015). Unfortunately, the lack of data on teachers' effort prevents us from investigating further along this direction.

Table 4.3: Program Impacts on School Inputs

	Infrastructures Index	Sports Facilities Index	Teacher Attendance Rate
	(1)	(2)	(3)
TREATED	0.045***	-0.007	0.009**
	(0.01)	(0.01)	(0)
Observations	261,517	278,779	289,564

Note: Standard errors are clustered on the district level. The analysis covers all 36 districts in Punjab-Pakistan. *p<0.1; **p<0.05; ***p<0.01

Table 4.4: Program Impacts on Components of the Infrastructures Index

	drink water exists	electricity exists	main gate exists	toilet exists	share of funct. toilets	building cond. is safe	boundary wall is complete
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TREATED	-0.001	0.001	0.008	-0.001	0.015***	0.074***	0.015**
	(0.003)	(0.012)	(0.005)	(0.003)	(0.004)	(0.015)	(0.007)
Observations	278,779	278,779	278,779	278,779	274,098	278,779	261,517

Note: Standard errors are clustered on the district level. The analysis covers all 36 districts in Punjab-Pakistan. *p<0.1; **p<0.05; ***p<0.01

4.5.3 Education Outcomes

Ultimately, we are interested in the effects on educational outcomes. Specifically, we examine the effects on education quantity, as measured by enrollment rate and student attendance rate, and education quality, as measured by the students' test score and reading/mathematical abilities. The results are presented in table 4.5.

In terms of education quantity, the NSB reform does not improve school enrollment (column 1). In fact, the effect is quite precisely estimated to be zero in that the point estimate -0.009 is very small and even the upper bound of its 95% confidence interval is only 0.018, a value that is 2% of the average enrollment rate before the reform. Regarding student's school attendance, the point estimates in column (2) to (5) suggest that the NSB reform increases the attendance rate of students from various school levels. However, the magnitudes are only nominal which are approximately 0.7% of the average attendance rate before the reform, suggesting that the impact on student attendance rate is nonexistent.

Regarding education quality, we do not find any impacts on children's mathematic and English reading abilities (column 6 to 7). While the point estimates are negative, suggesting that the NSB reform may even decrease the mathematic and English reading scores of children of age between 5 and 16 by 0.026 and 0.021 points, respectively, they are both statistically and economically insignificant (column 6 and 7). In comparison, the pre-reform mathematic and English reading scores for an average child are 2.4 and 2.2 points. Similarly, the effects are lacking for the fifth graders' test scores (column 8 to 9).

Overall, despite the significant increase in spending and the subsequent improvement in school conditions, we do not find policy impacts on education quantity and quality. This is largely consistent with the literature, which shows that improving physical inputs alone does not have meaningful impacts on education outcomes (see the review by Glewwe and Muralidharan 2016). One should keep in mind that our results are relatively short-term, and the lack of more detailed measures of human resources prevents us from a more comprehensive investigation into the human resources channel. Therefore, we cannot rule out the possibility of improvements in education outcomes through higher teacher effort or better school management in the long term.

Table 4.5: Program Impacts on Education Outcomes

	Enrollment	Student Attendance				Ability		Test Score	
	Currently Enr.	Primary	Middle	High	H.Sec	Math.	Eng.	Num.	Lit.
	(Age 5-16) (%)	(Gr.1-5)	(Gr.6-8)	(Gr.9-10)	(Gr.11-12)	(Age 5-16)		(Gr.5)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TREATED	-0.009	0.006	0.006	0.005	0.002	-0.026	-0.021	-0.087	-0.059
	(0.014)	(0.005)	(0.005)	(0.008)	(0.010)	(0.042)	(0.044)	(0.07)	(0.07)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
School FE	N	Y	Y	Y	Y	N	N	Y	Y
District FE	Y	N	N	N	N	Y	Y	N	N
Data Unit	Dist.	Sch.	Sch.	Sch.	Sch.	Dist.	Dist.	Sch.	Sch.
Observations	107	276,894	84,262	38,423	3,457	107	107	269,526	269,526

Note: Standard errors are clustered on the district level. The analysis covers all 36 districts in Punjab-Pakistan. *p<0.1; **p<0.05; ***p<0.01

4.5.4 Interpretation

Taken together, we find that the NSB reform has brought significant improvement in the conditions of school infrastructures and modest improvement in teacher's attendance. However, there is no meaningful impact on education quantity and quality. In light of Beasley and Huillery (2017), the lack of impacts on education outcomes is likely to be associated with the lack of capacity among the school council members who are held accountable for managing the grant. In fact, various reports on the education sector of Pakistan have consistently shown the lack of capacity of the school councils. A report on Punjab's education sector procurements by the Institute of Social and Policy Sciences (I-SAPS) shows that school council members from 64% of the public schools in Punjab are not familiar with the procurement rules and procedures for the school grant that they are responsible for, and 91% and 78% of the teachers report that they need training for financial management and school improvement planning, respectively (I-SAPS, 2014).

Although it is important to ensure a safe learning environment, it is not an effective way to improve enrollment and learning (Newman et al. 2002, Kremer 2003). And yet, we see that school infrastructures are the only outcomes that show meaningful improvement. We argue that the reasons are twofold. First, the significant improvement in school infrastructure conditions reflects the spending priority of the public schools. Public schools in Pakistan are often criticized for their poor infrastructure conditions and school security (Naviwala, 2015). This criticism reached to a peak after the school massacre in Peshawar district in 2014, where seven terrorists entered a public school by scaling the boundary wall and killed 132 schoolchildren (Sajjad et al., 2015). Improving the school buildings' conditions is a response to this widespread criticism. Second, although it has been realized in recent years that a better school does not equal better education, improving school infrastructures is still the focus of the education policymakers in Pakistan because it is regarded as a low hanging fruit for fixing the education crisis (Naviwala, 2019). And this perception of the policymakers is conveniently adopted and followed by the schools, especially by those with a school council that lacks capacity. The political connection of the public school teachers may also facilitate the transfer of this perception. In fact, many public school teachers have political patronage, and it is not uncommon that they play a dominant role when making school spending decisions (I-SAPS, 2014).

As it is agreed on in the literature, improving pedagogy is a promising way to improve education outcomes (Glewwe and Muralidharan 2016, Glewwe and Kremer 2006). While we find that the NSB reform has increased the teacher attendance rate by 0.9 percentage points, we doubt that this indicates teachers exert more effort to improve pedagogy. Actually, the magnitude of the impact is only nominal as it equals only 1 hour per month. If we take into account the issue of multigrade teaching, which is very common in Punjab, it is unlikely to see a sizable impact on student's learning.[10] Besides, it is not clear whether this additional hour per month was dedicated entirely to teaching as the government often assigns public school teachers to non-teaching duties, e.g., helping with anti-polio and anti-dengue drives, elections and administering government exams and surveys (Andrabi et al., 2008). Alif Ailaan (2014b), a research report based on in-depth qualitative interviews with 1,250 teachers from more than 600 schools in Pakistan, estimates that government teachers spend a quarter of the academic year on non-teaching activities. In fact, public school teachers in Pakistan are notoriously unmotivated in teaching and it has

[10]43 percent of public schools in Pakistan are multigrade (ASER, 2018)

been associated with an understanding that a child who goes to a public school will not have a chance in life, in terms of a job or being perceived as an equal (Naviwala, 2019). Holding teachers accountable is crucial but not easy in Pakistan. As it is mentioned, public teachers in Pakistan are unionized and are government employees who often have political patronage. There is no direct accountability relationship between teachers and parents who pay fees. Therefore, parents and school council do not have the power to fire a teacher for not delivering quality teaching. In fact, even a minister for education could not fire a teacher for not showing up to school (Naviwala, 2019). Furthermore, many teachers also offer private tutoring after school. It has become a norm for students in Pakistan to go to after-school tutors. Teachers have an economic incentive to compel students to sign up for tuition in order to learn material, or teachers may simply have less energy for teaching in school if they are primarily concerned with their tuition classes (Alif Ailaan, 2014b). Without a sufficient capacity to manage school grant and hold teachers accountable, school councils are unlikely to help improving education outcomes by just receiving a larger amount of grant.

4.6 Robustness Checks

4.6.1 Placebo Test

One compelling way to assess the "common trends" assumption underlying our identification strategy is to compare the temporal changes before the reform across different phases, i.e., a "placebo" test. We use two pre-reform years of the panel to conduct this placebo test. Specifically, our approach is based on the following specification:

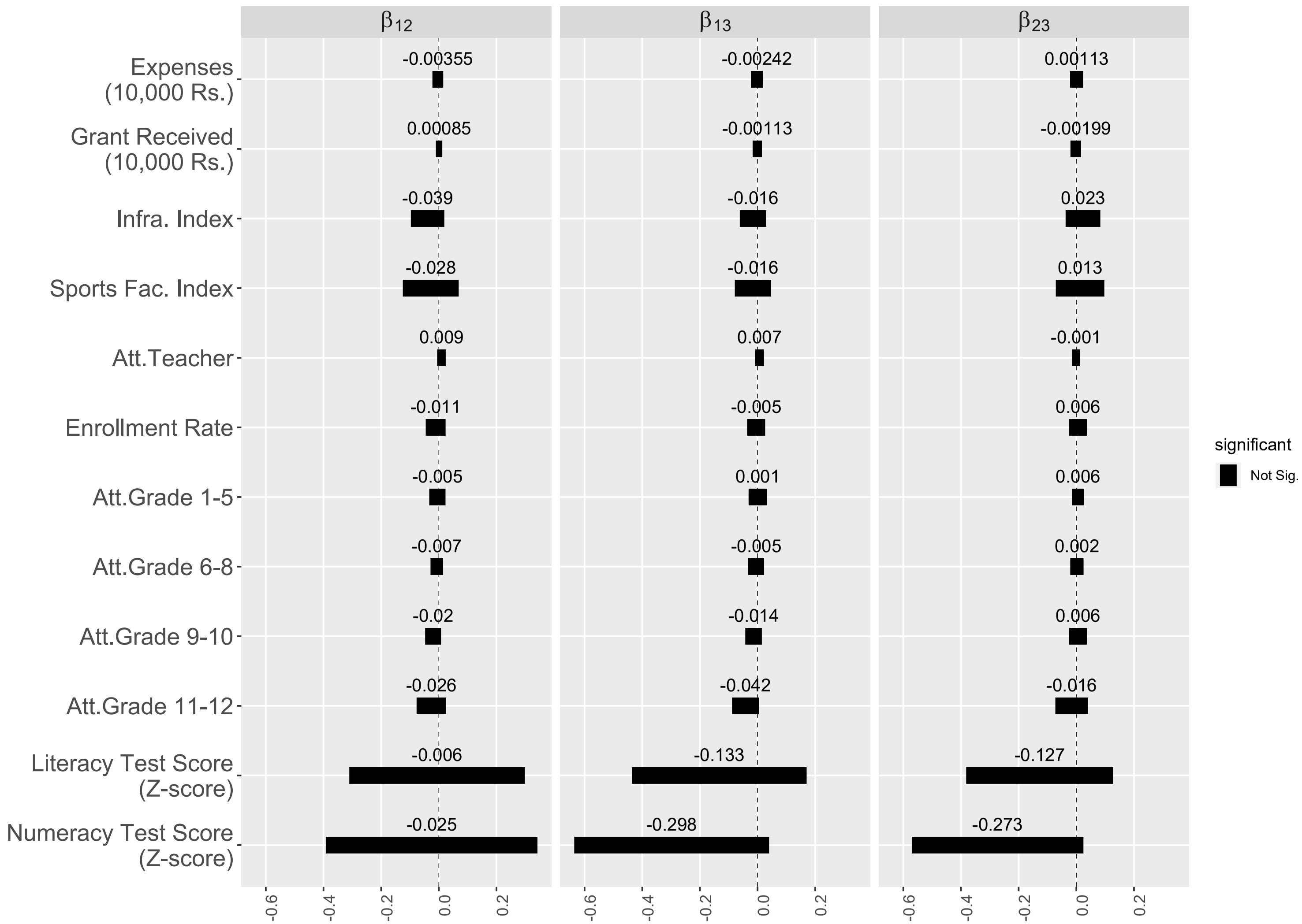
$$\begin{aligned} y_{sdt} = {} & \beta_{13} * PHASE1_d * PPOST_t + \beta_{23} * PHASE2_d * PPOST_t \\ & + \alpha_s + \gamma_t + u_{sdt} \\ \beta_{12} = {} & \beta_{13} - \beta_{23} \end{aligned} \tag{4.3}$$

where $PPOST_t$ is a pseudo-post dummy variable which identifies the latter of the two pre-reform years. Other variables' definitions remain unchanged. Therefore, β_{13} effectively captures the difference in the trend of phase 1 relative to phase 3. A similar definition is applied to β_{23} and β_{12}.

We conduct this placebo test on all outcome variables of our main analysis. We could not test on the English reading and mathematical ability scores because we only have one year of pre-reform data on these two variables. The point estimates and their corresponding 90% confidence intervals are presented in Figure 4.6, with β_{12}, β_{13} and β_{23} being plotted separately in different panels. Overall, we do not find any statistically significant difference in the trends across phases before the reform, i.e., the common trends assumption is satisfied. Furthermore, the point estimates are very precisely estimated as the confidence intervals are very narrow. This assures us that the zero point estimates are not a power issue.

4.6.2 Control for District's Effort on Information Updating

According to the reform committee, a district was selected into an early phase if the education officers (EOs) in that district were more responding to the education department in terms of information updating. This could be a confounder to our estimate of the reform's impacts if the district's effort on information updating is correlated with the improvement in school outcomes. The main channel for the EOs to collect the information of the schools is to visit the school in person. To control for this potential confounder, we obtain from the PMIU a school-level cross-sectional dataset which records the number of visits by EOs during the school year 2012/13, the school year just before the rollout of the NSB reform. We then calculate the yearly visit frequency for each school and aggregate to a district average. Then, we rank the districts by frequency of school visits in a descending order, division by division, i.e., the most visited district in a division is ranked at the first position of that division. We regard the rank of visit frequency as the proxy for the district's effort on information updating. The descriptive statistics of the visits by EOs are summarized by districts and reported in Table 4.7.



Note: standard errors are clustered at district level. Test score is standardized to mean of zero and sd. of 1 in that year. Infrastructures Index is an average of z-scores of eletricity, drinking-water, toilet, boundary-wall, playground, main-gate, satisfied-building-condition, boundary-wall-completeness dummies)

Table 4.6: Placebo Test

Table 4.7: Education Officers' School Visits by Districts

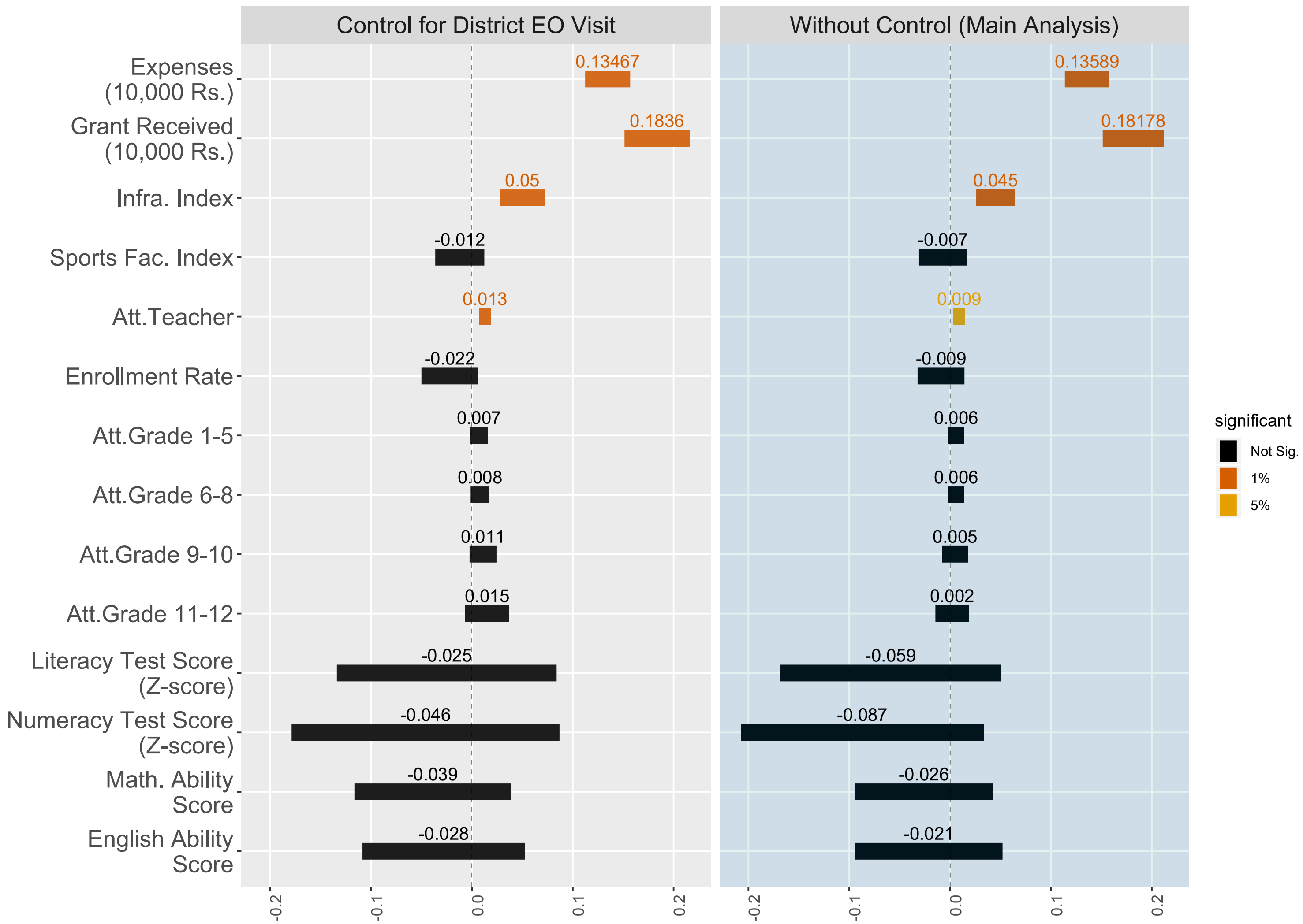
District	Nr. Visits	Ranking	Phase	District	Nr. Visits	Ranking	Phase
Bahawalpur Division				*Lahore Division*			
Bahawalpur	7.09	1	2	Nankana sahib	11.75	1	1
Rahimyar khan	5.8	2	1	Kasur	7.32	2	2
Bahawalnagar	5.6	3	3	Sheikhupura	6.51	3	3
Dera Ghazi Khan Division				Lahore	6.06	4	3
Muzaffargarh	8.86	1	1	*Multan Division*			
Dera ghazi khan	8.77	2	3	Khanewal	9.28	1	1
Rajanpur	5.99	3	3	Multan	8.86	2	3
Layyah	5.45	4	2	Vehari	6.22	3	2
				Lodhran	3.84	4	3
Faisalabad Division				*Rawalpindi Division*			
Chiniot	11.37	1	1	Chakwal	7.19	1	1
Toba tek singh	10.14	2	2	Rawalpindi	6.64	2	3
Jhang	9.8	3	3	Jehlum	5.17	3	3
Faisalabad	6.17	4	3	Attock	3.99	4	2
Gujranwala Division				*Sargodha Division*			
Hafizabad	9.74	1	3	Sargodha	13.37	1	1
Mandi bahauddin	9.07	2	3	Khushab	9.01	2	2
Gujrat	8.43	3	3	Mianwali	7.22	3	3
Sialkot	6.83	4	1	Bhakkar	5.57	4	3
Narowal	5.92	5	3	*Sahiwal Division*			
Gujranwala	5.52	6	2	Okara	8.47	1	1
				Sahiwal	7.13	2	3
				Pakpattan	5.64	3	2

Note: Nr.Visits is the average number of visits by EOs per year per school. Ranking is the ranking of Nr.Visits within a division.

We then interact the ranking of visits by EOs with the year dummies and add them to the specification (4.2). That is, we estimate the following specification,

$$y_{sdt} = \beta * TREATED_{dt} + \theta_\tau * Rank_d * D_t^\tau + \alpha_s + \gamma_t + u_{sdt} \tag{4.4}$$

where $Rank_d$ is the within-division rank of the school visit by EOs in district d in year 2012. D_t^τ are year dummies for year τ with τ = 2013, 2014, ..., 2017. The other variables' definitions remain unchanged. The point estimates of the effects, β, and their 90% confidence intervals are plotted in the left panel of Figure 4.8. For comparison, the results of the main analysis are plotted in the right panel. As we can see, controlling for the district's effort on information updating does not change the main results. In fact, the point estimates are extremely similar between the two specifications. In this regard, we conclude that the selection on district's effort on information updating does not bias our estimates of the policy impacts.



Note: Standard errors are clustered at the district level. In the left panel, we add district d's rank on the number of school visits by EOs at baseline, interacted with the year dummy variables as a way to control for the EOs' effort

Table 4.8: Control for Education Officers' (EOs) Effort

4.7 Conclusion

Whether providing decentralized grants to schools is effective in improving education quantity and quality remains a critical question for education policymakers. While the decentralized school grant has gathered popularity because it is arguably capable of reducing the mismatch between centralized provision and local needs, rigorous evaluations are still limited. We contribute to this limited literature by evaluating a large-scale policy, the "Non-salary Budget (NSB)" reform in Punjab, Pakistan, which increased the funding for non-salary expenditure by almost 10 times and made the school councils accountable for grant management. We find that the NSB reform has significantly increased the income and expenditure of the public schools in Punjab, resulting in a sizable improvement in the school infrastructures condition. Although we find that the reform has also improved teacher attendance rate, the magnitude of the effect is only nominal. Finally, we do not find any impact on enrollment rate, student attendance rate or test scores. We interpret the lack of effects on education outcomes as a result of insufficient capacity among the school council members. In fact, a report on the procurement in the education sector of Punjab, I-SAPS (2014), has revealed that the majority of school council members do not understand the procedure of school procurement. More importantly, the school councils have limited power to hold teachers accountable for delivering quality education, as teachers in public schools of Pakistan have political patronage. Simply increasing the funding of schools does not change the lack of accountability in the relationship between teachers and school councils. Overall, our findings are consistent with Mbiti et al. (2019) and Beasley and Huillery (2017) who both show that the effectiveness of decentralized school grants depends on the capacity of local planners who are responsible for grant management.

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