The impact of social health protection on migration: Evidence from Pakistan

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Abstract

We study the impact of social health protection on the decision to migrate by exploiting the Social Health Protection Initiative (SHPI), introduced gradually after 2015 in selected districts of Pakistan. We exploit the imperfect rollout of the program and evaluate the impact of the program on both international and inter-district out-migration. Employing the difference-in-difference method with district and year fixed effects, we find that enrollment in the SHPI program does not significantly affect international and overall inter-district migration. We further extend our analysis by separately investigating the migration patterns of urban and rural treated areas. We find that the introduction of the program has had no significant impact on the incidence of out-migration from rural areas. However, the impact of the program on out-migration from urban areas shows a negative and significant effect.

Keywords: *social health protection; Migration; Pakistan;Sehat Sahulat Program.*

JEL Classification: *I13; I15; O17; J21; J16.*

1 Introduction

The number of international migrants grew globally to 281 million in 2020, equivalent to 3.6% of the global population and another 750 million moves within national borders (IOM, 2022), with 73% of all migrants coming from developing countries (UN, 2019). This is the result of hoping for better earning opportunities and living conditions at the destination and, as such, is also a result of living conditions at home. To improve the situation for poor households, most developing countries have introduced different social assistance programs in the past couple of decades.[1] Among other social safety net programs, special emphasis has been given to achieving universal health coverage (UHC), which is reflected in the introduction of health insurance programs worldwide (Cotlear, Nagpal, Smith, Tandon, & Cortez, 2015) to minimize out-of-pocket health expenditures and facilitate utilization of health services for people living in poverty. Examples of such programs include Seguro Popular (SP) in Mexico, Rashtriya Swastiya Bima Yojana (RSBY) in India, the New Rural Cooperative Medical System (NRCMS) in China, and the Sehat Sahulat Program in Pakistan. In this paper, we investigate whether improving social health protection for low-income households can affect migration decisions. We do not only analyze the impact on international but also on internal migration. We furthermore differentiate between rural and urban migration, because we expect a better medical supply and thus the higher impact of social health protection in urban as compared to rural areas.

[1] In its report, World Bank (2014) identified that 119 countries have implemented at least one type of unconditional cash assistance program, and another 52 have implemented conditional cash transfer programs.

Recent literature has shown that social assistance programs can have a substantial effect on a wide range of social outcomes in addition to those that are specifically targeted by such programs. This includes many papers studying the impact of social assistance programs on migration outcomes (see for example Adhikari & Gentilini, 2018a; Hagen-Zanker & Himmelstine, 2013, for a comprehensive review). The main findings are that social protection policy can have a significant impact on the likelihood and pace of migration. According to Hagen-Zanker and Himmelstine (2013), this impact can be heterogeneous, with almost half of the reviewed papers showing that social protection program increases migration, while the other half shows a decrease in migration. While the majority of the studies were based on either conditional cash transfer programs (see for example Angelucci, 2004, 2012) or unconditional cash transfer programs (Ardington, Case, & Hosegood, 2009; Posel, Fairburn, & Lund, 2006), few studies analyzed the impact of social insurance on migration decision (see for example Sana & Hu, 2006; Sana & Massey, 2000). To the best of our knowledge, however, there is not a single study that specifically focuses on the impact of health insurance on migration decisions. We contribute to closing this gap in the current literature with our paper.

While most impact evaluations of health insurance programs focus on the utilization of health services (for example Anderson, Dobkin, & Gross, 2012; Helmsmüller & Landmann, 2022) and financial protection (Jütting, 2004; Wagstaff & Manachotphong, 2012), these programs might also have substantial impacts on the labor market (Dague, DeLeire, & Leininger, 2017; Ham & Ueda, 2020), child labor (Landmann & Frölich, 2015), and child's education outcomes (Alcaraz, Chiquiar, Orraca, & Salcedo, 2017). To the best of our knowledge, however, there is not a single study available that explicitly evaluates the impact of health insurance on migration decisions. Given the importance of social health protection around the globe and that our theoretical considerations (see Conceptual Framework) suggest a distinct effect of health insurance on migration compared to other social programs, such as cash transfer programs, this constitutes a substantial gap in the literature.

In a recent study, Bazzi (2017) has identified two countervailing effects of social assistance programs on migration decisions: opportunity cost and liquidity constraints. The opportunity cost will motivate the household member not to leave his or her geographical location because mobility is associated with an opportunity cost in addition to the direct cost that would be incurred by the household if they decide to migrate. On the other hand, the liquidity constraint channel might ease the cost constraint of the household with the introduction of social assistance programs, and the then financially disadvantaged household can now think about migration if the other requirement of the migration decision is met. Similarly, according to Adhikari and Gentilini (2018b), social safety net programs that may influence migration decisions are classified as follows: i) Measures that implicitly facilitate migration by mitigating liquidity constraints and transaction costs ii) Programs that implicitly discourage migration via conditional cash transfers to the local residents in order to convince them not to leave the present residents iii) programs that are explicitly conditioned on spatial mobility (e.g., housing vouchers in an inner-city neighborhood in the United States and rural-urban transportation subsidies in Bangladesh). To conclude, the social assistance program might have different socio-economic impacts, including an impact on migration decisions, even if the program is not specifically designed to serve as a migration policy.

In this study, we exploit a recent health insurance program introduced in Pakistan to analyze its impact on international and inter-district migration. The program was introduced in the Khyber Pakhtunkhwa (KP) province of Pakistan on December 16, 2015, and later rolled out in selected districts in the rest of Pakistan. Initially, only the poorest 21% of the population in four selected districts of KP province were eligible for the program. In August 2016, the program was rolled out in all the districts of KP, and the poverty threshold was relaxed, now making the poorest 51% of the province's population eligible for the program. In its third phase, the eligibility criteria were further relaxed, making the poorest 69% of the province's population eligible for the program, corresponding to 2.48 million families. In parallel to the program implemented in KP, the federal government of Pakistan also introduced the program under the name of the National Sehat Sahulat Program. The program was launched in 2015, and more than 3 million families from 38 districts all across Pakistan were enrolled in the program based on a poverty line of US $ 2 per day.

The staggered implementation of the program across districts and the availability of districts, which never received the intervention, provide a very good basis to evaluate its impact. We define those districts in which the program has been rolled out as the treatment group and those districts without the intervention as the control group. Also, since the program was not introduced uniformly, we can exploit differences in the utilization rate of health insurance between districts to define two different treatment intensities: high-treated and low-treated districts. We then build a panel data set in the district level, including treatment status, migration outcomes, and district-level controls. We obtained administrative data on international migration from the Bureau of Emigration and Overseas Employment (BEOE), Pakistan. Further, we constructed inter-district migration rates from the Labor Force Survey (LFS), conducted regularly by the Pakistan Bureau of Statistics (PBS). The survey data also allows us to build further control variables. We then use a fixed effect model to relate the partial introduction of the social health protection program to changes in migration patterns, in the spirit of a difference-in-difference approach. We find that the public health insurance program had no significant impact on international migration and also do not find significant effects on inter-district migration. Differentiating migration from rural and urban areas, we do not find a significant impact on out-migration from urban and rural treated districts.

The rest of the paper proceeds as follows: Section 2 discusses the migration and socioeconomic status of Pakistan, followed by a section describing the Social Health Protection Initiative in Pakistan. Section 4 includes the conceptual framework that discusses the theoretical linkages between social health protection and its impact on migration decisions, followed by a Data & Methodology section, and Section 6 discusses the results of our study before we conclude the study in Section 7.

2 Conceptual Framework

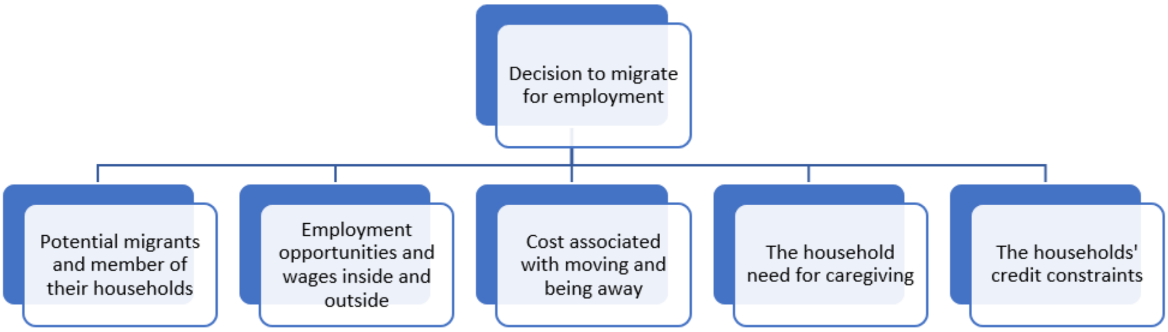
To acquire a thorough knowledge of the impact of social protection programs on migration decisions, it is necessary to first clarify the varied interpretations of social protection used by various organizations. According to the World Bank, social protection programs are government efforts that assist people, families, and communities in efficiently managing income-related risks, to reduce vulnerability and reduce income fluctuations. These initiatives also aim to improve consumption stability and promote equitable outcomes. The International Labor Organization (ILO) defines social protection programs as the provision of benefits to households and individuals through public or collective arrangements, with the primary goal of protecting against deteriorating living standards or the threat of such decline.

Following the definitions presented by different organizations, now we will discuss the conceptual framework of the impact of social protection on migration decisions and then try to build a theory on how social health protection might affect migration decisions. To better understand how a social protection program can influence migration decisions, first, we will look into the determinants of migration decisions. The determinants of migration were first analyzed by Harris and Todaro (1970), where the authors were curious about the factors influencing aggregate migration movements from rural to urban regions. According to them, the urban-rural wage differential turns out to be one of the most significant factors in aggregate migration flows. Later, migration was viewed as a household-level decision in which the household attempted to maximize welfare by maximizing income through migration while minimizing risks. The decision to migrate depends on quite a lot of factors, broadly categorized as "push" and "pull" factors (see for example Mayda, 2010; Simpson, 2022; Vogler & Rotte, 1998).

Sabates-Wheeler and Waite (2003), introduced the concept of migration as one of many informal coping strategies adopted by the household to minimize risk or as a response to shock. Economic theory predicts that the availability of other informal coping strategies, such as social protection or health insurance, might also affect migration decisions, and the direction of the decision will be determined by the cost associated with migration compared to the expected benefits of it (Hagen-Zanker, Siegel, & de Neubourg, 2009). The introduction of migration as one of many informal coping strategies opens up a black box where the economist are now more interested in investigating the impact of social protection programs (also coping strategies) on migration decisions (see for example Chau, Kanbur, & Qin, 2014; da Mota Silveira-Neto & Azzoni, 2009; Deshingkar, Wood, & Béné, 2015) including two review articles (Adhikari & Gentilini, 2018b; Hagen-Zanker & Himmelstine, 2013).

Ardington et al. (2009) analyzed the labor supply decision of large social transfers and find out that large cash transfers to the elder age population in a household, in terms of pension receipt, make the prime-aged adult more likely to be employed specifically through migration. According to them, the decision to migrate within a household depends on the following factors: the potential migrants and members of their household,

Figure 1: Factors influencing migration decision



source: *Ardington et al. (2009)*

employment opportunities and wage differentials, the cost associated with moving and being away, the household's need for caregiving, and the household's credit constraints.

The first and foremost important factor in Figure 1 is that the potential migrant member and his or her household members will decide whether the migration of a household member is feasible or not. Secondly, the migration decision also depends on the employment opportunity and wage differential between the home country and the destination country. If the wage differential is higher, the likelihood of migrating will also increase. The third factor is the cost associated with migration. Migration is a risky investment that involves both direct and indirect costs (opportunity costs). If the cost associated with migration is higher than the expected benefit of migration, then the potential migrants in the household might not opt for migration. In a developing country, the migration decision might also be affected by the presence of a dependent (child or elderly) population in a household. If a household has a dependent population, it will have a negative impact on the mobility of its members, given that the member who opted for migration is the only prime-aged adult in the household. The last factor, according to the author, is the household's credit constraints. These five factors are important to better understand the conceptual framework of how a social protection program can influence migration decisions. According to Gazeaud, Mvukiyehe, and Sterck (2020), social protection programs can influence migration decisions through four basic mechanisms presented below. The important thing to note here is that the conceptual framework to be presented below is not specifically related to the impact of social health protection on migration but is more into social protection programs and migration. As discussed above, this is the first study evaluating the impact of social health protection on migration decisions, which is why we will build our theory based on the closest available conceptual framework present in the literature.

- **Opportunity Cost**: This mechanism operates effectively when the program's eligibility is contingent upon the household member's physical presence. For example, if an individual within the household qualifies for health insurance only when resid-

Figure 2: Mechanism through which social protection program influence migration decisions

source: *Gazeaud et al. (2020)*

ing in a designated geographic area, and that person decides to relocate either to a different region within the country or abroad, he or she will forfeit the benefits that he or she would have received in the household member's presence.

- **Liquidity Constraint**: Since we know that migration is a risky investment that involves direct costs on top of the opportunity cost discussed above, If the household is financially constrained and the social protection is not conditional on physical presence, enrollment in such social protection programs might reduce the financial constraint, allowing the financially disadvantaged household to invest in migration. In that case, enrollment in the social protection program increases the likelihood of a household member migrating.

- **Collateral Channel**: Collateral channel means that the household receiving a social assistance grant, for instance, cash transfer throughout let's say one year can take advantage of this program by negotiating with the credit lending institutions. Angelucci (2015) studied the impact of an exogenous, temporary, but guaranteed income shock on the migration decisions of Mexicans to the United States. According to the study, entitlement to such social assistance programs increases migration, even though the money received through social assistance is consumed elsewhere.

The study also found that the new migration comes from previously financially constrained individuals and households. In such cases, the individual or household uses the program entitlement as proof of expected income to better negotiate with the credit institutions to finance the migration.

- **Risk Aversion**: Finally, the last mechanism, according to Gazeaud et al. (2020), is the risk aversion channel. Since migration is a risky investment, entitlement to a social protection program might enhance the migration flow for those individuals or households whose preferences are characterized as decreasing absolute risk aversion (DARA) and restraining those whose preferences are characterized as increasing absolute risk aversion (IARA).

Since we have discussed in detail the conceptual framework of how a social protection program can influence migration decisions, we will now discuss which of the channels are relevant in our settings. The liquidity & collateral mechanisms might not be super relevant in our settings because we are evaluating the impact of social health protection, which only covers inpatient hospitalization of the enrolled households. The liquidity mechanism might only be relevant for households with higher health needs while the collateral mechanism might only be effective in social protection programs like conditional cash-transfers programs. Similarly, the credit constraint mechanism is also not very relevant in our setting and might only be effective in programs like conditional and unconditional cash transfers. The opportunity cost mechanism is relevant in our setting because the decision to migrate would cost that specific individual or household foregone benefits in terms of health insurance, on top of the direct cost associated with migration. One of the relevant mechanisms that Gazeaud et al. (2020) did not mention in the conceptual framework, and rightly so because of the different design of the program, is the caregiving mechanism. The current literature suggests that informal caregiving might have a substantial impact on the labor market outcomes of the caregiver (see for example Bolin, Lindgren, & Lundborg, 2008; Carmichael & Charles, 2003; Van Houtven, Coe, & Skira, 2013). In a developing country setting, this mechanism is very important to consider while deciding to migrate. A typical household in Pakistan needs at least one adult member available in the home or the near vicinity of the home, to take care of the elderly and also the children. With the introduction of health insurance programs, the need for caregiving might also reduce because of better health outcomes for the dependent population (elderly and children), which can be reflected in enhancing the migration decision.

The second half of this study is to analyze the impact of social health protection on internal (inter-district) migration. Similar to the mechanisms presented above, the opportunity cost mechanism will work as a pull factor for out-migration (inter-district), and hence the people living in treated districts are expected to be less likely to migrate to untreated districts. Having said that, one cannot rule out the incidence of intra-district and/or inter-district migration within the treated districts. It makes absolute sense if a household or family migrates from one treated district to another or from one region to another within the same treated district. On the other hand, the caregiving mechanism might still have a positive impact, and people living in treated districts might have better health outcomes including that of the dependent population, which could potentially decrease the caregiving responsibilities of the household. The decrease in caregiving responsibility might have an impact on the inter-district migration decision of the household members. Hence, the impact of health insurance on inter-district migration could be both positive and negative depending on what type of migration you are looking for and of course on the effect size of the two countervailing effects.

Since more health facilities are available in urban centers, it is essential to differentiate the out-migration from urban and rural treated regions. Although the program has been rolled out based on exogenously given poverty scores across Pakistan, where the eligibility threshold has been kept the same for all districts and regions, however, access to health facilities varies across districts and regions. A family living in a big urban city will benefit more from enrollment in a health insurance program as compared to a family living in a rural area. A counter-argument to the above statement could be that since the government implemented the health insurance program in the entire province, and the poor people living in far-flung rural areas can now afford free inpatient hospitalization, incentivizing healthcare providers to invest also in far-flung rural areas, and thus people who would have moved to urban centers to get access to better health facilities can now stay in their original place of residence and get the similar treatment. Speaking to the media on the occasion of the launching ceremony of the Naya Pakistan Sehat Card for Punjab province, the then prime minister of Pakistan can be quoted as saying that

> ”Now the government will not spend money to build hospitals, rather a private sector will build hospitals in rural areas **(GulfToday, 2021)**”

3 Migration Status of Pakistan

Pakistan is a low- to middle-income country (LMIC) in South Asia with an estimated population of more than 224 million in 2021 (5th largest in the world), of which 82.83 million live in urban areas and the remaining 141.96 million live in rural areas. Migration and the export of manpower remain the key elements of focus, especially in developing countries. Pakistan, being the fifth-most populous country in the world, remains the second-largest country in South Asia in terms of manpower export. According to the report on exporting manpower by the Board of Emigration and Overseas Employment, approximately 12.85 million emigrants were registered with the board between 1971 and 2020. Out of the total, almost 96% of these emigrants moved to gulf countries followed by 1% each to other middle eastern countries, Africa and Malaysia. During the year 2020, a 64% decline has been witnessed in the number of registered emigrants, from 625,203 emigrants in 2019 to 224,705 emigrants in 2020, primarily because of the COVID-19 outbreak. The occupational group-wise statistics of international emigration show that approximately 2% of the registered emigrants are highly qualified followed by 3.6% highly skilled emigrants, 42% skilled emigrants, 9.2% semi-skilled, and 42% unskilled labor. In 2021, Pakistan received 31 billion dollars in remittances, accounting for about 8.9% of its entire Gross Domestic Product (GDP). Remittances and export revenue play an important role in Pakistan's balance of payment (Bureau of Emigration and Overseas Employment, 2020; Bureau Of Statistics, 2017). The number of Pakistani labor migrants has increased significantly during the previous decade and a half. However, this pattern has shifted since 2013. The number of Pakistani employees who travel overseas each year has decreased from 622,714 in 2013 to 382,439 in 2018. According to a report published by the International labor organization, the representation of women in the migration flow is quite low, constituting only 0.21% of the total, which amounts to 6,444 individuals (ILO, 2018). This disparity can be attributed to the 1979 Emigration Rules, which stipulate that the minimum age for women to work abroad as domestic workers are 35 years, limiting their opportunities for regular migration. According to a recent report published by Bureau of Emigration and Overseas Employment (2020), more than 51% of the emigrants came from Punjab followed by 25% from Khyber Pakhtunkhwa and almost 10% from Sindh province.

Besides international migration, domestic migration from low (urban) to high-productivity (urban) regions has been a key driver of structural change and growth. For instance, the reallocation of labor from agriculture to non-agricultural industries between 1978 and 2003 may be credited with around 26% of the aggregate productivity growth in China (Dekle & Vandenbroucke, 2010). Similarly, in Pakistan, almost 8% of the population, on average, are engaged in inter-district migration and is contributing to the livelihood of their families. Table 3 includes all the relevant information on inter-district migration e.g.; average inter-district migration, the proportion of migration from urban and rural areas, and the proportion of migration in the last 4 years. The table also includes demographic information at the district level. The majority of the rural workforce migrated to big urban cities for better job opportunities and higher wages.

4 Social Health Protection Initiative in Pakistan

In an attempt to improve the health outcomes of the residents of Khyber Pakhtunkhwa and to achieve Universal Health Coverage (UHC), the provincial government of Khyber Pakhtunkhwa (KP) was the first among the four provinces to launch a publicly financed health insurance scheme with the name "Sehat Sahulat Program", initially for the poorest 21% of the residents of four pilot districts in KP. The eligibility was determined by the proxy means test (PMT) score, and those households whose PMT score was less than or equal to 16.17 in those selected districts were eligible for the program. The following phase saw a degree of flexibility in the qualifying standards, as indicated by the raising of the PMT score cutoff from 16.17 to a range less than or equal to 24.5. Furthermore, the initiative's scope has been greatly expanded to include the whole province of Khyber Pakhtunkhwa. With this comprehensive expansion, which includes extending its reach to all districts and simplifying the qualifying standards, the program covered the most economically disadvantaged 51% of the province's population. In its third phase, the eligibility criteria were further relaxed by increasing the PMT cutoff score to less than or equal to 32.5, making 69% of the residents of KP eligible for the program. Together with relaxing the PMT cut-off score, in its third phase, the SSP has changed the definition of enrollment from household to family. A typical household might have more than one family, but a family consists of only a husband, wife, and unmarried children. Recently, the KP government extended the program to all the permanent residents of the province and changed the name of the program from Sehat Sahulat to the Sehat Card Plus program. The primary focus is not only to provide universal access to the residents of KP to have their treatment done from quality healthcare facilities but also to abate poverty by decreasing out-of-pocket (OOP) expenditure for health (Hasan, Mustafa, Kow, & Merchant, 2022). It is one of Khyber Pakhtunkhwa's government premier initiatives. An insurance provider chosen through a national competitive bidding process is carrying out the program. As a result, more than 7.2 million KP families are receiving free inpatient healthcare treatments. The beneficiary families' data is taken from the National Database Regulatory Authority (NADRA). Up to a maximum of Rs. 1 million per family each year, services are provided to recipients completely free of charge. The program incur an annual cost of about 18 billion to the provincial government (Government of Khyber Pakhtunkhwa, 2022).

After successfully implementing the program by KP's provincial government, on 09 December 2020, the SSP program has expanded to the largest (by population) province of Pakistan i.e; Punjab. The plan of the provincial government was to provide the Sehat Insaf card to families in all 36 districts of Punjab. Soon after the introduction of SSP in Punjab, the then Prime Minister announced the extension of the SSP program to the residents of Azad Jammu & Kashmir on December 28, 2020. As of September 21, 2022, 37 million families were enrolled in the program, and an estimated number of visits to the hospitals crossed 5 million.

Since the enactment of the 18^{th} constitutional amendment, it has been the responsibility of the provincial governments to provide health services; however, the federal government has supported a number of health-related projects through the Public Sector Development Programmes (PSDP) in order to advance the Sustainable Development Goals (SDGs) and improve the nation's general health status. PSDP funds totaling Rs 20,193.9 million were given for 71 health sector projects, including the national SSP, during FY2021. The national SSP, a historic healthcare effort launched by the federal government, aims to pave the way for Universal Health Coverage (UHC) in the country. The program is not only a social health protection initiative that contributes to accomplishing the "National Health Vision 2016-2025," but it also demonstrates a paradigm shift in how the government provides healthcare to the general population in both public and private hospitals. In a nutshell, it is a program for the poor that allows them to access medical treatment promptly and respectfully without having to worry about paying for it (*Pakistan Economic Survey*, 2022).

5 Data and Methodology

5.1 Data

In this section, we will present a brief overview of all the different data sets we will be using in this paper. For our analysis, we will be using four types of data sets across the study year. The insurance utilization data has been taken from the administrative data, which covers the eligibility, enrollment, and claims data of residents of the Khyber Pakhtunkhwa (KP) province of Pakistan. The insurance data of the districts outside of KP has been taken from the report of the Central Management Information System (CMIS) of the Federal Sehat Sahulat Program (*National Sehat Sahulat program*, 2019).

The administrative data on international migration, which is collected by the Board of Emigration and Overseas Employment (BOEO) in Pakistan, is utilized for analyzing the impact of social health protection on international migration(Bureau of Emigration and Overseas Employment, 2020). The household survey of Pakistan, i.e., the Labor Force Survey (LFS), is used to analyze the impact of social health protection on inter-district and regional migration. Furthermore, the advantage of using household-level survey data is that we can exploit household-level information, which can then be used as a control variable in our analysis. The complete information about the data sets used in this paper is presented in the subsections below.

5.1.1 KP Sehat Sahulat Program Administrative data

This section includes information on the unique administrative data set of the Sehat Sahulat Program initiative in the Khyber Pakhtunkhwa province of Pakistan. The administrative data of KP's SSP program can be further classified into three sub-categories.

1. Eligibility Data
2. Enrollment Data
3. Claims data

Based on the PMT cut-off score, which was less than or equal to 32.5 at that time, almost 2.5 million households were eligible for the Sehat Sahulat Program. Since the enrollment has been made on a household head basis, we do have some demographic information about the eligible household heads. Almost 80% of the eligible household heads are male while approximately 95% of the eligible household heads reported as "Married" and another 3.7% of the eligible household heads reported as "Widowed" when asked about their marital status. The average age of the eligible household head in our sample is 48.76 years. The enrollment data set contains information about the enrolled households in Khyber Pakhtunkhwa Province, Pakistan. The enrollment campaign for the SSP program started in January 2016 and enrolled almost 1.48 million households by November 2018. During that period, 90% of enrollment was already done by June 2017. The enrollment data contains detailed information about the geographic location of the household enrolled, the date on which the household was enrolled, and the encrypted ID's of the household. Although the geographic information of the enrolled household is very detailed and one can estimate the aggregate enrollment per village, in our paper we are interested to evaluate the effect at the district level so we merged the enrollment data by districts of KP. It is pertinent to note here that we have enrollment data only until November 2018.

Regarding the claims data, more than 200 thousand claims were reported during the period from February 2016 up until February 2020. The claims data is also very detailed where one can figure out the information about treatment type, treatment cost, admission date, and discharge date, etc. It also includes information on the treatment localities e.g.; in which district the treatment took place. It is not necessary that a household enrolled in a specific district can only do his/her treatment in that district. One can freely move between treated districts for better healthcare provision. Despite the fact that the insurance card was issued on the IDs of household heads only, other household members can also utilize the insurance card of his/her household head and could get medical treatment. Using the unique encrypted IDs of the household head, we are able to merge the enrollment data with claims data, though not 100%. Again, special care has been taken to merge the two data sets. The reason for not being able to merge the complete claims data with the enrollment data is very obvious. Since not all the treatment has been done by the main card-holder but their household members can also get the treatment on the same card, we cannot identify the enrollment information of those individuals who do not belong to the group of main card-holders. We were able to merge 52% of the claims data with enrollment data, indicating that 48% of the claims have been made by household members and not by household heads. In order to capture the complete claims picture per district, we upscaled the aggregate claims per district by a factor of 2 so that the non-merged claims data can be compensated.

5.1.2 National Sehat Sahulat Program data

In this section, we will go over the National Sehat Sahulat Program's data set in depth. Since we know that the health insurance program was originally implemented in KP in December 2015, specifically for KP province, the federal government also took the initiative and launched the National Sehat Sahulat Program. The national SSP was introduced in selected districts throughout Pakistan based on the PMT cut-off score of 32.5 or less. According to National SSP (2018), approximately 24 million population and 4.78 million families, across Pakistan, were eligible for this program. Out of the total eligible families, approximately 1.2 million families were identified as valid families. Valid families are defined as the total number of eligible families which have been transferred by the National Database Regulatory Authority (NADRA) to the State Life Insurance Corporation (SLIC) of Pakistan and have a valid national identity card. Out of the total, 963,836 valid families were enrolled in the program. The proportion of total enrolled families out of total valid families is 80% while the proportion of total enrolled families out of total eligible families is 63% and a total of approximately 15 million population were enrolled in the program.

In total, 36 districts across Pakistan took part in this program. Punjab, being the biggest province of Pakistan, in terms of population, contributed the most to the list of enrolled districts where 17 districts were enrolled in the program followed by Khyber Pakhtunkhwa province, which enrolled 6 districts in the program. The number of districts enrolled in Sindh, Balochistan, Azad Jammu & Kashmir (AJK), and Gilgit Baltistan (GB) are 4,5,2, and 2, respectively. The coverage of the program is not uniformly distributed by gender where male coverage, on average, stands at 55% while female coverage is only 43%. However, when talking about utilization rate, the statistics are 40% for females and 35% for males. In the national SSP program, the Annualized Utilization Rate (AUR) [2] for each district is calculated by dividing the Projected Annualized Admissions (PAA) [3] by the Total Enrolled Families(TEF). The study district's overall utilization rate for each distributed card stands at 2.8%.

5.1.3 Bureau of Emigration and Overseas Employment

The Bureau of Emigration and Overseas Employment (BEOE) operates as a centralized entity, controlling Pakistan's emigration process and procedures. The yearly report of the BEOE includes provincial, district, category-wise, and occupational group-wise information of all the registered emigrants of Pakistan. The data set available online includes information starting from 1971 till June 2023. In our district-level analysis, this data set serves our purpose as it includes district-level emigrants information during our study period. We took advantage of the district-by-year administrative emigration data starting from 2013-14 till 2020-21 to evaluate the impact of health insurance, introduced in Pakistan, on international migration. One of the limitations of using this dataset is that it does not report any socioeconomic information about the districts. Because of data limitations, we can only run a standard diff-in-diff analysis without controlling for any covariates. This dataset is only used in one of the specifications where we evaluate the impact of health insurance on emigration.

5.1.4 Labor Force Survey of Pakistan

Every alternate year, the Pakistan Bureau of Statistics (PBS) conducts a household survey called the Labor Force Survey (LFS) of Pakistan. To study the impact of health insurance on inter-district migration, we use five rounds of the LFS survey of Pakistan from 2013-14 till 2020-21. Information regarding labor force participation, inter-district migration, age profile, education level, and other socio-economic and demographic characteristics are taken from labor force surveys and the same data is aggregated at the district level for

[2]
$$\text{Annualized Utilization Rate} = \frac{\text{Projected Annualized Admissions}}{\text{Total Enrolled Families}}$$

[3]
$$PAA = \text{Cumulative Admissions up to current underwriting month} * \left(\frac{12}{\text{Passed Months}}\right)$$

our analysis.

It is important to note that the district-level identification was not readily available in the LFS survey until 2020-21. A comprehensive exercise was conducted to compute district identifiers from a 10-digit code given to each Primary Sampling Unit (PSU). For instance, each household was coded with a long 10-digit code which includes the information of the respondent's province, district, whether the respondent belongs to urban or rural areas, and so on. Using the coding explanation of each round of the LFS survey, we have computed the district identifier for each individual respondent of the survey. After computing the district identifiers, we then aggregated the data of our variables of interest to the district level. For example, we have created a variable, indicating migration status, from a question where every respondent was asked to report from where he/she migrated if he/she answered the question that he/she has not been living in the current district since birth. Again the information regarding the district from which the individual migrated, was not available. Instead of a district name, a seperate code was allocated for each district which was not similar, structurally, to the the district code given to each primary sampling unit. After several consultations with the Pakistan Bureau of Statistics (PBS), the relevant information for the migrated districts was collected, and then another extensive exercise to construct migrated-district codes that are aligned perfectly with the district codes given in the primary sampling unit framework. During the exercise, we were not only able to construct a variable for migration status but also constructed different variables like from which region the participant has migrated and which region he/she is living in at the moment. These kinds of variables were constructed to analyze the impact of health insurance on inter-district migration from different to different regions. For instance, we are interested in figuring out if the people are moving from treated/untreated rural regions to treated/untreated urban regions or vice versa.

Out of the total, districts that started the social health protection initiative and have claims data will be taken as treated districts, and districts that did not start the health insurance program will be considered as control districts. In total, 454 (district-level) observations have been included in this study, excluding Balochistan, Gilgit Baltistan (GB), and Azad Jammu & Kashmir (AJK). The reasons for excluding these regions from our analysis are the following. For Balochistan, each administrative division is taken as a separate stratum in the LFS survey while in other provinces, each administrative district is taken as a separate stratum. In that case, we might not have enough representation of each district of Balochistan in the survey data. Another reason for excluding Balochistan is that the migration numbers are very low in the majority of the districts including some districts where the inter-district migration has been reported as 0. The reason for excluding GB and AJK is that only 2 districts from these regions are included in the national SSP program. Out of the total observations, 273 observations are from the control group and 215 are from the treated group. The pre-treatment observations are 180 while the post-treatment observations are 274. The reason behind more observations from the post-treatment period is that we have included 03 post-treatment periods in our analysis while there are only 02 pre-treatment periods in our analysis. A detailed descriptive statistics table is presented which includes district-aggregated migration information, demographic information, and information related to education outcome (see Table 1 for reference).

5.1.5 Treatment variables

As discussed above, those districts that are enrolled in the social health protection initiative are considered as treated districts and those that are not, are considered as control districts. Based on the insurance utilization information, treatment intensities in both KP and the rest of Pakistan have been calculated. The utilization rate of the program was calculated by dividing the number of claims per district by the district population. The utilization rate seems to be very low, as, on average 1.6 persons in every 1000 district residents get their medical treatment done using the program. One of the reasons might be that the program was not implemented for the entire district population and only after August 2016, the PMT score criteria were increased to 24.5, which made only 51% of the residents eligible for the program. The second argument is that the program is only entitled to inpatient services and the inpatient hospitalization rate is very low in Pakistan. In simple words, out of the total enrolled population, only a few percent would have health care needs, and only a few percent of those will get into the hospitals and if they are admitted to the hospitals, will be covered by the health insurance program. According to Helmsmüller and Landmann (2022), the incidence of hospitalization did not increase with the introduction of the program in the KP province of Pakistan. With only 51% of the population covered, and a low hospitalization rate coupled with a lack of knowledge about the program, it is unrealistic to expect a high rate of program utilization.

Control districts consist of those districts who are not been enrolled up until now. To better understand how the program has been expanded throughout Pakistan, two district-level maps have been presented in Figure 3 by utilizing the administrative data of the program. The left panel shows the share of the enrolled population in the program up until 2020 while the right panel shows the annual utilization of the program until 2020. We can see that the majority of the dark-shaded districts in the left panel belong to the KP province. There are two reasons for this, The first is that the program was first introduced in KP province in 2015 and soon after the introduction, the eligibility criteria were relaxed to a PMT score less than or equal to 24.5 which already made 51% of the residents of KP eligible to the program. The second reason is that all the districts of KP are enrolled in the program while only the selected districts from other provinces are enrolled in the national program.

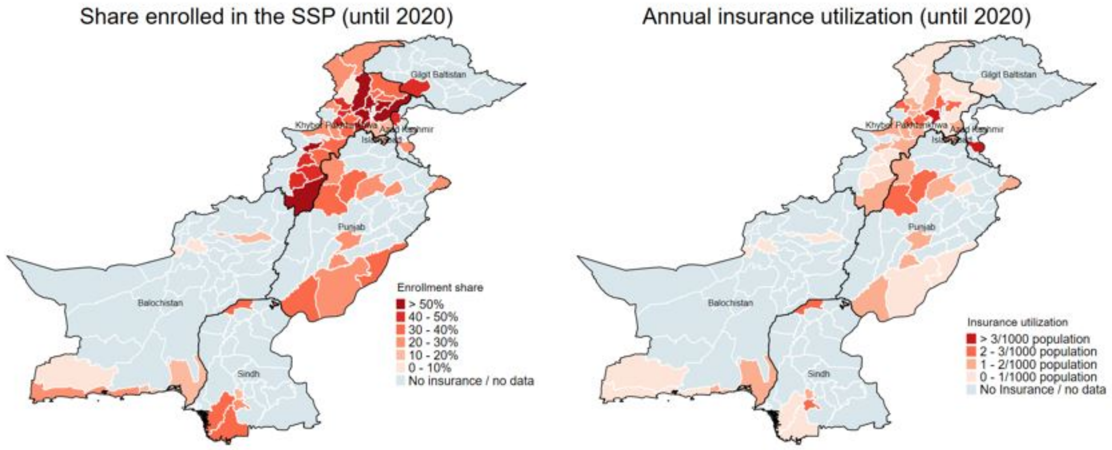
5.2 Econometric Specification

Our main objective is to identify the effect of the publicly financed health insurance scheme, introduced in Pakistan in 2015, on international and inter-district migration. Understanding the program's design is very important to figure out which identification strategy one should use. For instance, the provincial program is introduced initially in 4 pilot districts

Table 1: District level baseline descriptive statistics

	Treatment Status			
	Control Districts		Treated Districts	
	Date of the sample		Date of the sample	
	2013-14	2014-15	2013-14	2014-15
Frequency	47	47	40	41
international migration	0.003	0.004	0.004	0.005
	[0.003]	[0.004]	[0.006]	[0.007]
inter-district migration	0.077	0.072	0.071	0.073
	[0.036]	[0.035]	[0.033]	[0.034]
migration from rural	0.046	0.044	0.045	0.047
	[0.029]	[0.029]	[0.025]	[0.028]
migration from urban	0.031	0.028	0.025	0.026
	[0.017]	[0.017]	[0.020]	[0.017]
migration in last 4 years	0.209	0.217	0.241	0.246
	[0.067]	[0.076]	[0.083]	[0.079]
labor force participation	0.316	0.322	0.304	0.307
	[0.050]	[0.050]	[0.088]	[0.091]
age	22.886	22.930	22.148	22.293
	[1.818]	[1.772]	[1.649]	[1.719]
young-cohort	0.750	0.748	0.763	0.759
	[0.029]	[0.030]	[0.031]	[0.033]
productive-cohort	0.173	0.176	0.162	0.166
	[0.020]	[0.021]	[0.025]	[0.024]
old-cohort	0.077	0.076	0.076	0.075
	[0.020]	[0.020]	[0.018]	[0.019]
primarty education	0.611	0.604	0.663	0.652
	[0.100]	[0.096]	[0.057]	[0.059]
secondary education	0.216	0.222	0.164	0.176
	[0.095]	[0.088]	[0.055]	[0.057]
higher education	0.173	0.174	0.172	0.171
	[0.020]	[0.022]	[0.024]	[0.019]
female	0.490	0.492	0.498	0.494
	[0.018]	[0.018]	[0.026]	[0.023]

Figure 3: National enrollment & utilization of the SSP



Source: Own calculation based on administrative data from KP and the federal SSP program

Note: *The above maps show the proportion of the population enrolled in SSP and insurance utilization across Pakistan. The left map shows that the share enrolled can be as low as 10% of the population and can be as high as more than 50% of the population. The right-hand side map shows insurance utilization, calculated by dividing projected annualized admissions by the total population in that specific district. The average utilization rate is around 1.5/1000 population and the maximum is 4.5/1000 population. In total, 53 districts are enrolled in this program across Pakistan. Out of 53, 26 districts belong to KP and 27 to the rest of Pakistan*

and then later on expanded to the whole province of KP in a staggered manner. Also, the eligibility criteria were initially fixed at a 16.17 PMT score for those 4 pilot districts, covering only 21% of the poorest population. Later on, the eligibility criteria were relaxed step-wise and in 2020 the then Prime Minister announced that all the residents of the KP province are enrolled in the provincial health insurance program. On the other hand, the national SSP was introduced in selected districts of Pakistan, including districts from KP. A specific proportion of the population was eligible for the program based on PMT scores. Also, not all the districts are rolled out at once, but the districts have been rolled out in a staggered manner (see SHPI for details).

In the recent literature, it can be seen that in most of the impact evaluation studies, two methods are used quite often i.e; Regression Discontinuity design (Lee & Lemieux, 2010) and Difference in Difference Estimation (Goodman-Bacon & Marcus, 2020). The fact that the rollout of the program did not happen at once, but rather step-wise, we can say that the program did not follow a sharp design. In such cases, Regression Discontinuity Design (RDD) is not the best choice. The staggered intervention, both in terms of enrolled districts and proportion of the population within enrolled districts, make it a favorable case for us to adopt difference-in-difference analysis in our paper (see for example Del Valle (2021): Karan and Mahal (2019): & Dague et al. (2017) for a more recent application of diff-in-diff).

The treatment status of a district is determined by whether the district belongs to KP (because by now, all the districts of KP are rolled out in KP's SHPI program) or if the district belongs to other provinces, whether that specific district is covered in the national

SSP program or not. In other words, all the districts of KP, excluding Ex-FATA[4], which are considered treatment districts together with selected treated districts from the rest of Pakistan. Our baseline identification strategy uses difference-in-differences to estimate the impact of social health protection initiative on both international as well as inter-district migration.

$$\mathrm{y}_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t \cdot (\mathrm{year_t} * treat_i) + \gamma X_{it} + \sigma_i + \theta_t + \mu_i \tag{1}$$

whereas,
– $year_t$ is the set of year dummies
– $treat_i$ is a dummy variable with a value of 1 if the district is treated and 0 otherwise
– $year_t \cdot treat_i$ is our main indicator of interest indicating the treatment effect at different points in time
– X_{it} is a set of control variables (Age & Education categories)
– σ_i is the district fixed effect
– θ_t is the time-fixed effect

After estimating the effect on international as well as inter-district out-migration using the above specification, we have constructed variables for out-migration from urban and rural areas. The rationale for constructing these variables is that the effect of the program on out-migration from urban areas is expected to be larger than the effect on out-migration from rural areas. The expectation is based on the fact that the opportunity cost of moving out from an urban treated area is higher than moving out from rural treated areas because one can exploit the program more efficiently in urban areas through access to quality healthcare facilities. One can indeed get free access to quality health care in rural areas, but the number of empanelled hospitals and the quality of services provided by these facilities differ, to a great extent, from the quality of services provided by empanelled facilities in urban areas.

In the labor force survey of Pakistan, information regarding the current location of the internal migrants and his/her previous location can be traced through an extensive process. For example, we have information for each district regarding the inflow of migrants and his/her previous district of residence. Also, the information on whether the previous place of residence was located in an urban or rural area is present. For instance, if I want to calculate the variable "mfu_{it}" for the district "Peshawar", a district located in the Khyber Pakhtunkhwa province of Pakistan, the following exercise needs to be done. First, I need to trace out, in every district, the number of inflow of migrants from Peshawar. Then for each district, the probability of selecting that specific household which has reported that they have migrated from Peshawar is given through which I calculated the estimated number of in-migrant from Peshawar to each district and then later on summed it to get an aggregated number of out-migrant from Peshawar. This exercise has been repeated for all the districts to get an estimated number of out-migration. Similarly, out-migration from rural

[4]Federally Administered Tribal Areas, commonly known as FATA, was a tribal region in the North Western region of Pakistan. In 2018, the FATA was merged with its neighbouring province i.e.; Khyber Pakhtunkhwa through the 25th amendment to the constitution of Pakistan

vs out-migration from urban is calculated by taking the share of estimated out-migration from rural/urban from a specific district in the total district population. The formula for international out-migration, inter-district out-migration, out-migration from urban, and out-migration from rural can be written as:

- **International out-migration**

$$y_{it} = \frac{\text{No of international out migration from district } i \text{ at time } t}{\text{Total population of district } i \text{ in 2017}} \tag{2}$$

- **Inter-district out-migration**

$$y_{it} = \frac{\text{No of inter-district out migration from district } i \text{ at time } t}{\text{Total population of district } i \text{ in 2017}} \tag{3}$$

- **Migration from urban areas**

$$mfu_{it} = \frac{\text{No of inter-district out migration from urban area of district } i \text{ at time } t}{\text{Total population of district } i \text{ in 2017}} \tag{4}$$

- **Migration from rural areas**

$$mfr_{it} = \frac{\text{No of inter-district out migration from rural area of district } i \text{ at time } t}{\text{Total population of district } i \text{ in 2017}} \tag{5}$$

To analyze the impact of social health protection in Pakistan on out-migration from rural and urban areas, we have employed the same econometric specification as above, but now the dependent variable will change from inter-district out-migration to inter-district out-migration from urban and inter-district out-migration from rural areas. we can test the hypothesis by either analyzing the program's impact on the difference between urban vs rural out-migration or by doing sub-group analysis for both out-migration from urban and out-migration from rural.

$$\text{mfu}_{it} - \text{mfr}_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t \cdot (\text{year}_\text{t} * treat_i) + \gamma X_{it} + \sigma_i + \theta_t + \mu_i \tag{6}$$

$$\text{mfu}_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t \cdot (\text{year}_\text{t} * treat_i) + \gamma X_{it} + \sigma_i + \theta_t + \mu_i \tag{7}$$

$$\text{mfr}_{it} = \beta_0 + \sum_{t=1}^{4} \beta_t \cdot (\text{year}_\text{t} * treat_i) + \gamma X_{it} + \sigma_i + \theta_t + \mu_i \tag{8}$$

Whereas, the $treat_{low_i}$ group consists of 125 districts in total, based on the cut-off score of 0.0012 utilization rate. $treat_{high_i}$ group consists of 120 districts in total. After making a panel of 5 rounds of LFS survey, we have 672 district-level observations in which 245 (125 districts in $treat_low$ & 120 districts in $treat_high$) districts belong to treatment groups and the rest of the 427 districts belong to the control group. As mentioned previously, we have included a vector of time-varying district-level covariates in our main specification, the descriptive statistics of which are present in Table 1. We have also included detailed estimation results of low & high treatment districts in A.3 & A.4 of the Appendix section.

One might argue that there is a significant difference between the healthcare facilities, available in urban areas compared to rural areas and programs like Sehat Sahulat can better be utilized in areas where the facilities are far better. It means, that the impact of the health insurance program might also affect our variable of interest differently. For instance, moving out from a well-developed treated urban district to a treated/non-treated rural district might have a significantly higher opportunity cost in terms of forgone health insurance, compared to those who are currently living in rural-treated areas and want to move to either untreated or treated urban areas. Exploiting the labor force survey of Pakistan, following an exhausting exercise, we have managed to construct variables for different movements. For example, we were able to construct a variable for the participants who moved from urban and rural areas. Moreover, we further exploited the information and constructed variables that tell us from where the participants are moving and whether they are moving from treated to untreated or vice versa. The detailed estimation results of the impact of health insurance on inter/intra region movement are also included in table A.1 & A.2 of the Appendix section of the paper.

6 Results

In this section, the results of our main specification, using different data sets will be presented in detail. It is important to note that we study the impact of social health protection initiatives in Pakistan on both international and inter-district migration. In the first step, the impact of the program on international out-migration has been evaluated followed by the impact on inter-district out-migration. Following the results of inter-district out-migration, some heterogeneous analysis has also been added where the impact on out-migration from rural as well as urban areas is studied.

6.1 Impact on International migration

The first outcome we examine, using the BEOE data set is the impact of the program on international migration. Since this data set does not have detailed information about the other characteristics of the districts, we cannot control for any observable in this model. We can only control for time-fixed effects and district-fixed effects. The results, showing the impact of health insurance on international migration, are presented in Figure 4 given below. We can see that the treatment effect in the period 2013-14 is not statistically significant, indicating the common pre-trends between control and treated groups. The coefficients on Treat 2017-19 - Treat 2020-21 show the Average Treatment Effect (ATE) at different periods. The reason for including the treatment effect separately for each post-treat period is that some districts enrolled earlier than other districts, and we are expecting a differential treatment effect for early-enrolled districts compared to later-enrolled districts.

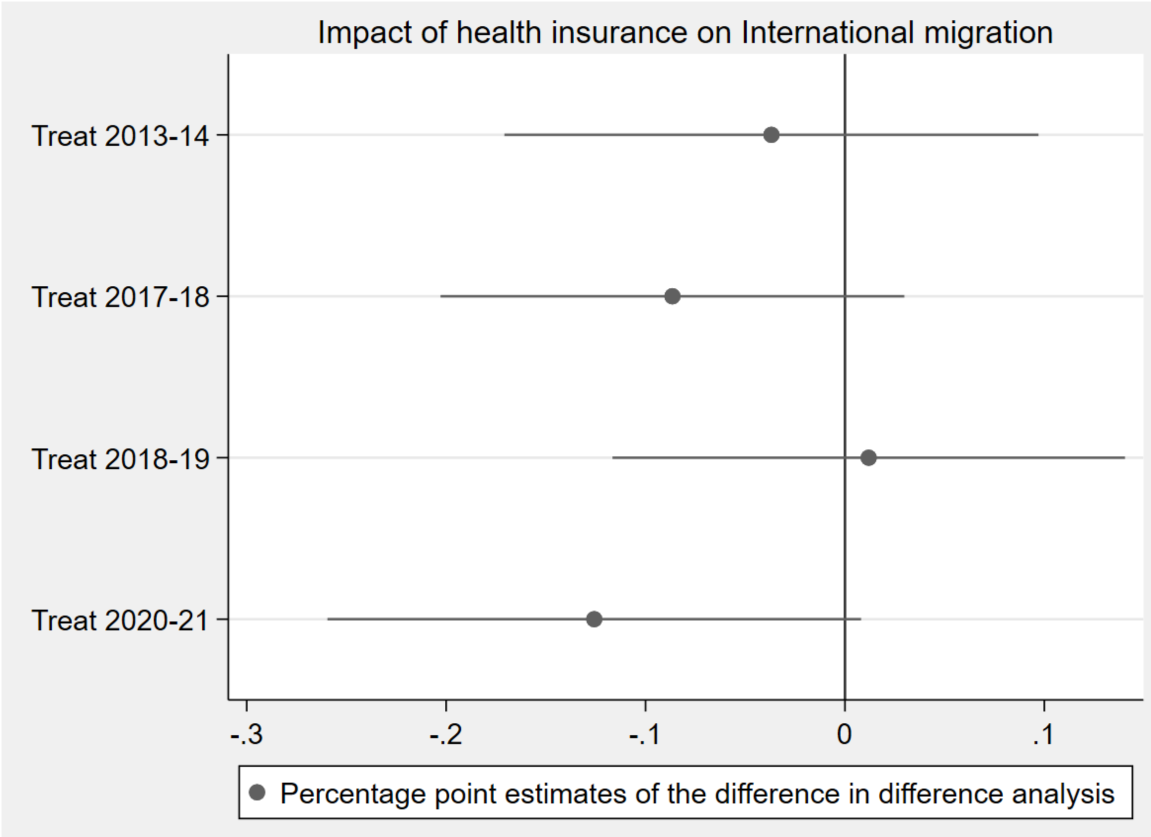


Figure 4: *The above graph shows the percentage point estimates of the impact of social health protection initiative on international migration using the specification mentioned in equation 1. Since the administrative data does not have district-level information about the demographic variables, we cannot include demographic and other control variables in this analysis*

We can observe from Figure 4 that health insurance does not have a significant impact on international migration using a two-way fixed effect (TWFE) difference-in-difference analysis. The results suggest that there is no significant difference in the behavior of households living in treated districts as compared to households living in control districts, in terms of their decision of international migration. Since the program has not been rolled out all across Pakistan, and during the study period, only the poorest segment of the population was eligible for the program, and the fact that the program is only for inpatients, we should not be expecting a big impact in terms of international migration decisions.

6.2 Impact on inter-district migration

It will be interesting to analyze the impact of the health insurance program on internal migration. The effect of this program on internal migration might be significantly greater than the impact on international migration. International migration requires a lot of financial resources in the beginning, keeping in mind the targeted population that is enrolled in the insurance program, their decision to migrate might be influenced more by their credit constraint rather than whether or not they are enrolled in the program. However, it would be interesting to see whether there is any impact of the program on internal migration. Since the BEOE data does not have information about other district characteristics, including internal migration, and only keeps a record of the number of registered emigrants per district who moved abroad, we cannot estimate the effect on internal migration using the same BEOE dataset. To estimate the impact of the Social Health Protection Initiative on internal migration, we have exploited the Labor Force Survey (LFS) conducted, each alternate year, by the Pakistan Bureau of Statistics (PBS). Since the survey is very detailed and includes household-level information regarding demographics, health status, etc., we can exploit the information given in the survey and control our model for different confounding factors.

As we can see in Figure 6, we have included a standard two-way fixed-effects diff-in-diff model, controlling for time and district fixed effects, together with all the other control variables. We can see that our model satisfies the parallel pre-trend assumptions where the coefficient of $Treat2013-14$ is not statistically significant, indicating that pre-trends of both control and treated groups were parallel. The other three treatment coefficients show the treatment effect at different points in time. We can see that there is no significant impact of health insurance on inter-district migration.

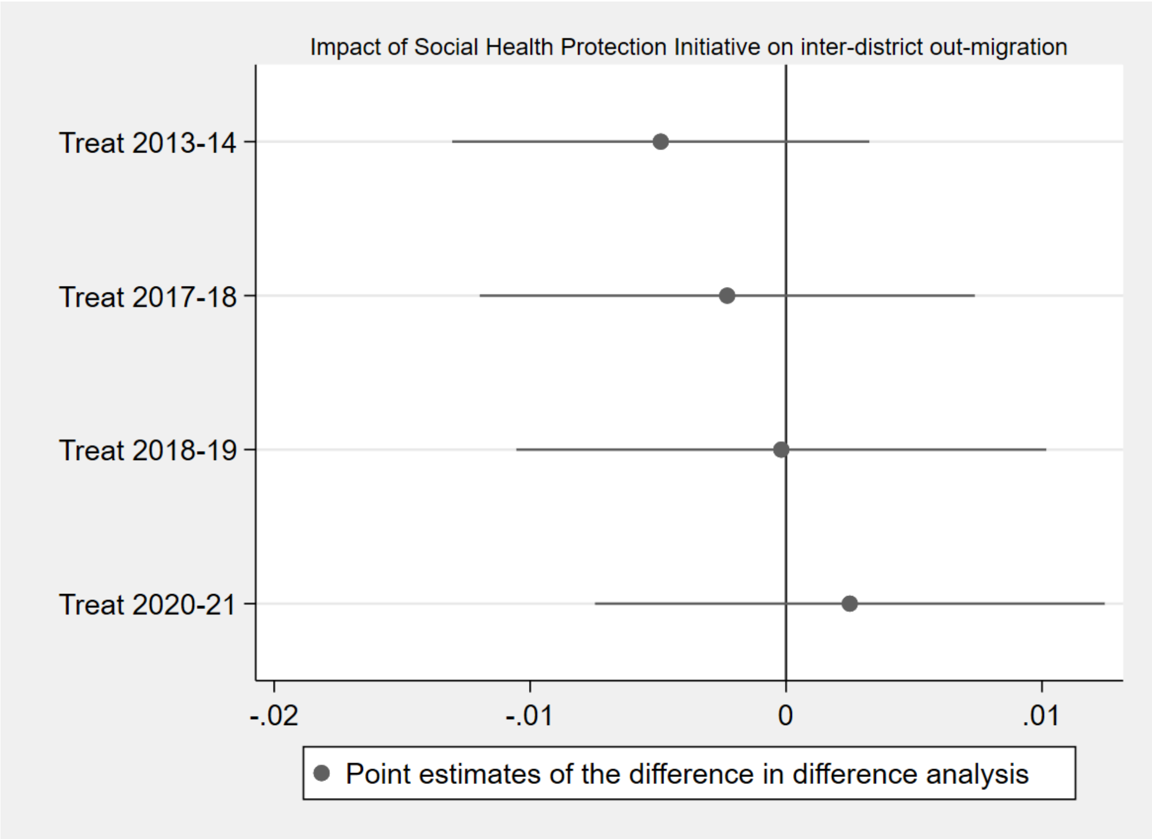


Figure 5: *The above graph shows the points estimates of the impact of the Social Health Protection Initiative on inter-district out-migration using the specification mentioned in equation 1. Since we are using a household-level survey called the Labor Force Survey conducted by the Pakistan Bureau of Statistics, we can control for socio-economic variables. We have controlled the model for age categories and education categories.*

The findings presented above indicate that the social health protection initiative implemented in Pakistan lacks a notable influence on both internal and international out-migration. One contributing factor to this limited impact could be attributed to the program's low utilization. The initiative was not initially extended to the entire population, and its coverage was restricted to inpatient treatment exclusively. Consequently, the utilization rate remained minimal, averaging 1.5 per 1000 people. This assertion can be corroborated by examining a geographical representation illustrating district-wise insurance utilization relative to the enrolled population. Observing the map reveals that the highest utilization per 1000 enrolled individuals is approximately 13%. However, despite enrollment figures exceeding 50% in certain districts, the actual utilization rates remain comparatively low (see Figure B.1 in the Appendix B.1).

We expect a differential impact of the program on out-migration from urban vs rural areas and went one step further to analyze separately, the impact of the program on urban and rural out-migration. A more strong and more negative effect of the program in urban areas is expected because one can exploit the program more efficiently in urban areas with better health facilities compared to rural areas. To test this hypothesis, in the following sections we will present the results of the impact of the program on out-migration from urban and rural areas.

6.3 Impact on urban vs rural migration

In this section, before proceeding to analyze the impact of the program on out-migration of both urban and rural areas separately, we have estimated equation 6 to test our assumption of differential treatment effect in urban vs rural areas. In equation 6, we have subtracted the out-migration from the urban areas in the district 'i' at time 't' from the out-migration from rural areas in district 'i' at time 't'. To validate our argument of differential treatment, the impact of the program on the difference between urban and rural areas out-migration should be significant with negative coefficient signs. The estimation results of the difference between urban and rural out-migration are presented in the figure given below.

we will analyze the impact of health insurance on urban out-migration. Following the results from the above sections, this analysis will present the results with a full set of control variables. Figure 6 will present the estimation results of the impact of the program on out-migration from urban areas. In this estimation result, we again control our model for district and year fixed effect together with all other control variables i.e. age-categories, and education categories. As we can see from the estimation results, health insurance does not have a significant impact on out-migration from urban areas. One can expect a negative impact of health insurance on out-migration from urban areas because the opportunity cost of moving out from an urban treated area is more than the rural treated area. Furthermore, we have also included the estimation result for treatment intensities which is given in the appendix section.

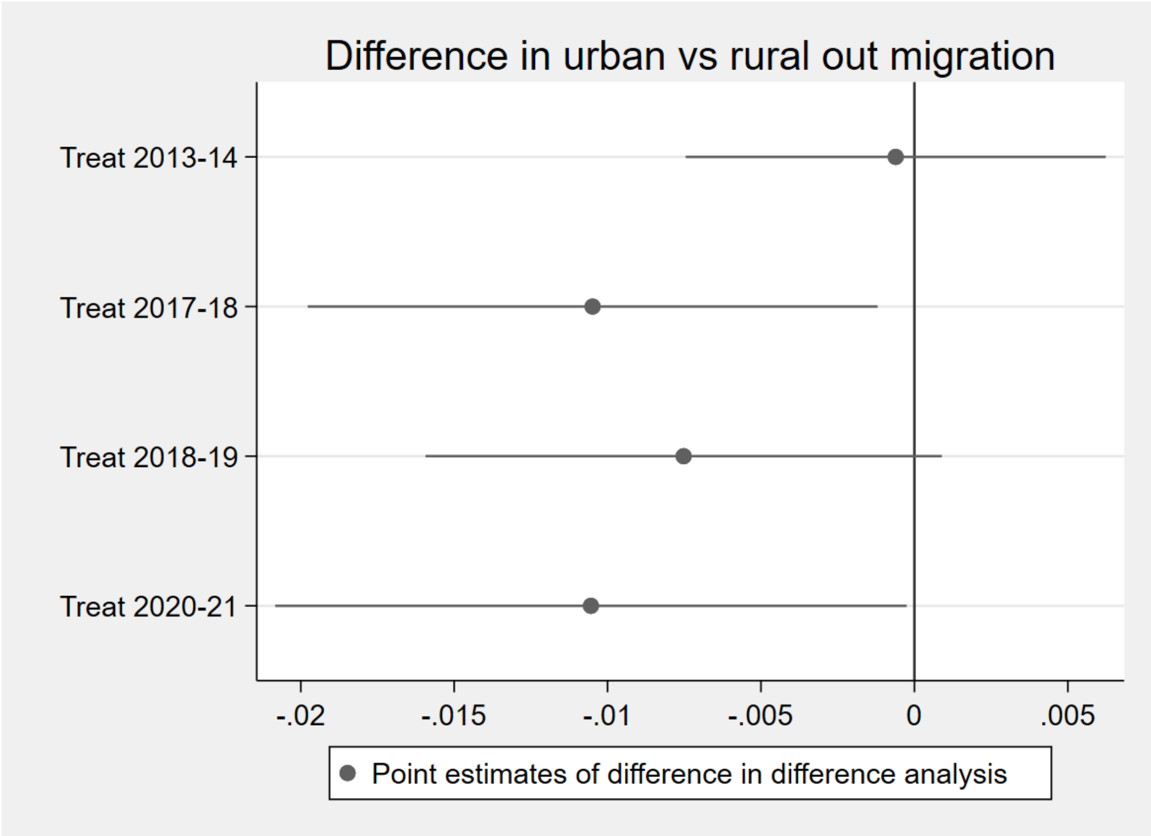


Figure 6: *The above graph shows the point estimates of the impact of the Social Health Protection Initiative on the difference of urban vs rural out-migration using the specification mentioned in equation 6. Since we are using a household-level survey, called the Labor Force Survey (LFS), conducted by the Pakistan Bureau of Statistics (PBS), we can control our model for socio-economic variables. We have controlled the model for age and education categories.*

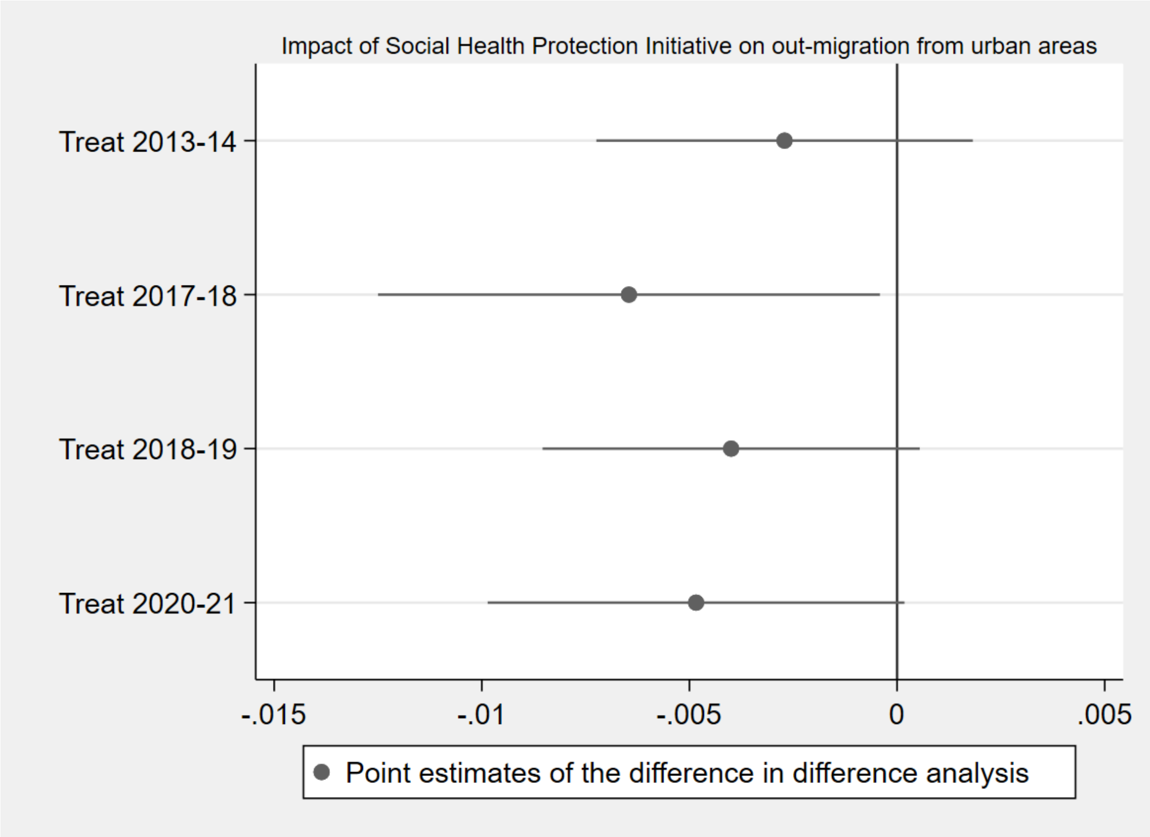


Figure 7: *The above graph shows the points estimates of the impact of the Social Health Protection Initiative on inter-district out-migration from urban areas using the specification mentioned in equation 7. Since we are using a household-level survey called the Labor Force Survey conducted by the Pakistan Bureau of Statistics, we can control for socio-economic variables. We have controlled the model for age categories and education categories.*

Finally, we have estimated the impact of health insurance on out-migration from rural areas. One can expect a positive impact, if any, of public health insurance on out-migration from rural areas because of two reasons. The first reason is that the healthcare provision facilities in urban areas are comparatively better than those in rural areas, so there is an incentive for moving out from rural areas towards urban areas to get better healthcare facilities. The second reason is that, with the introduction of health insurance programs, the health outcomes of the dependent population improve, which can be reflected in reducing the caregiving responsibilities of the household, making room for out-migration. Keeping in mind these two mechanisms, we went one step further and analyzed the impact of health insurance on out-migration from rural areas. Following the previous specifications, a complete set of control variables together with district and year fixed effects are included while estimating the coefficients presented in table Figure 8 given below.

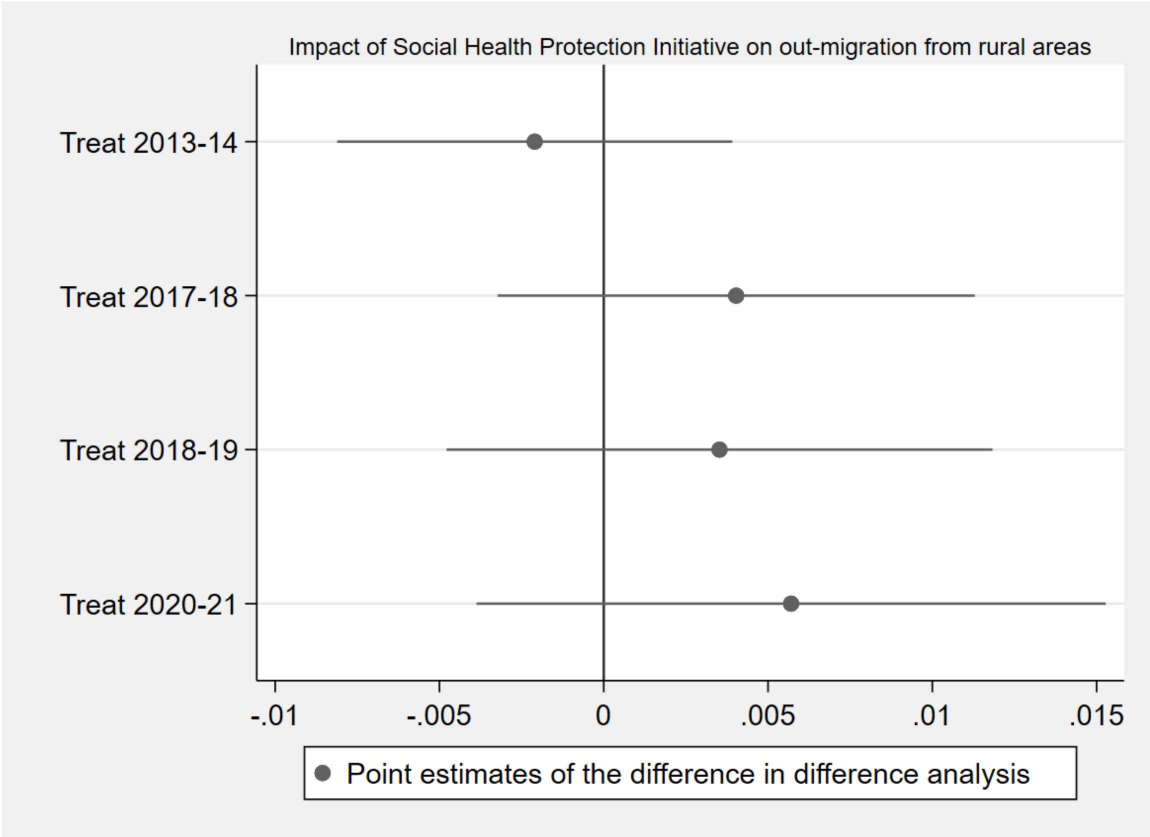


Figure 8: *The above graph shows the point estimates of the impact of the Social Health Protection Initiative on inter-district out-migration from rural areas using the specification mentioned in equation 8. Since we are using a household-level survey called the Labor Force Survey conducted by the Pakistan Bureau of Statistics, we can control for socio-economic variables. We have controlled the model for age categories and education categories.*

7 Conclusion

The impact of social protection programs on migration decisions has been widely studied. The current literature suggests that social protection programs affect both international and internal migration, depending on the design and requirements of the program. However, little has been investigated to determine social health protection's impact on migration decisions. To estimate the impact of social health protection on domestic & international migration, we exploit the recently introduced Social Health Protection Initiative (SHPI) in Pakistan (see section SHPI for detail).

The impact evaluation of the program on out-migration has been carried out using the specification mentioned in equation 1. To test the basic assumption of the standard diff-in-diff, the year 2013–14 is taken as a post-treated period, while in reality, the program only started functioning in early 2016. The estimated treatment effect in the years 2013–14 is not statistically significant, implying that our model is satisfying the pre-trend assumption of the standard diff-in-diff estimation technique. By utilizing the difference-in-difference estimation technique, we find that enrollment into the program does not significantly affect international and inter-district migration. Furthermore, going one step further, when we analyze the program's impact on out-migration from rural areas, we do not see a statistically significant impact. However, the impact of the program on out-migration from urban areas is statistically significant with negative signs. The negative sign of the coefficient indicates that enrollment into the SHPI program, on average, reduces the out-migration from treated urban areas compared to the control group. In terms of coefficient signs, the results are consistent with what we discussed in the conceptual framework section of the paper. As discussed in the previous sections, one can expect a positive sign on the coefficient of out-migration from rural areas while the opposite is true for out-migration from urban areas.

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A Additional estimation results

Table A.1: Regression Analysis of Inter-district out-migraiton from urban areas

	(1) **Average Migration**	(2) **Migration from Urban**	(3) **Urban to Urban**	(4) **Urban Urban-Treat**	(5) **Urban Rural-Treat**
Treat 2014-15	0.005	0.003	0.004**	-0.001	0.001
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
Treat 2017-18	0.002	-0.004	-0.004	-0.000	0.001
	(0.006)	(0.004)	(0.003)	(0.001)	(0.001)
Treat 2018-19	0.002	-0.003	-0.004	-0.001	0.001
	(0.007)	(0.004)	(0.003)	(0.001)	(0.001)
Treat 2020-21	0.007	-0.002	-0.003	-0.001	0.001
	(0.005)	(0.003)	(0.002)	(0.001)	(0.001)
Observations	408	408	391	350	408
R^2	0.876	0.855	0.748	0.555	0.814
District FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
age cohort	YES	YES	YES	YES	YES
educ categories	YES	YES	YES	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Regression Analysis of Inter-district out-migration from rural areas

	(1) **Migration from Rural**	(2) **Rural to Rural**	(3) **Rural Rural-Treat**	(4) **Rural Urban-Treat**
Treat 2014-15	0.003	0.001	-0.000	0.002
	(0.003)	(0.002)	(0.002)	(0.002)
Treat 2017-18	0.006	0.005	0.003	0.003*
	(0.004)	(0.003)	(0.002)	(0.002)
Treat 2018-19	0.004	0.007*	0.004*	-0.000
	(0.005)	(0.004)	(0.002)	(0.001)
Treat 2020-21	0.008	0.009**	0.004**	0.001
	(0.005)	(0.004)	(0.002)	(0.002)
Observations	408	408	395	408
R^2	0.881	0.808	0.732	0.801
District FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
age cohort	YES	YES	YES	YES
educ categories	YES	YES	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Regression Analysis of Inter-district out-migration from urban areas with treatment intensities

	(1) **Average Migration**	(2) **Migration from Urban**	(3) **Urban to Urban**	(4) **Urban Urban-Treat**
Low-Treat 2014-15	0.003	0.004	-0.001	0.001
	(0.003)	(0.003)	(0.001)	(0.001)
High-Treat 2014-15	0.002	0.004**	0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Low-Treat 2017-18	-0.007	-0.006	-0.000	0.001
	(0.005)	(0.005)	(0.001)	(0.001)
High-Treat 2017-18	0.001	0.001	-0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Low-Treat 2018-19	-0.005	-0.006	-0.001	0.001
	(0.005)	(0.004)	(0.001)	(0.001)
High-Treat 2018-19	0.000	-0.001	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)
Low-Treat 2020-21	-0.004	-0.004	-0.001	0.001
	(0.003)	(0.003)	(0.001)	(0.001)
High-Treat 2020-21	0.001	-0.001	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Observations	408	391	350	408
R^2	0.858	0.753	0.561	0.815
District FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
age cohort	YES	YES	YES	YES
educ categories	YES	YES	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Regression Analysis of Inter-district out-migration from rural areas with treatment intensities

	(1) **Migration from Rural**	(2) **Rural to Rural**	(3) **Rural Rural-Treat**	(4) **Rural Urban-Treat**
Low-Treat 2014-15	0.002	0.001	-0.001	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
High-Treat 2014-15	0.003	0.002	0.001	0.002
	(0.005)	(0.004)	(0.003)	(0.002)
Low-Treat 2017-18	0.005	0.004	0.002	0.003*
	(0.005)	(0.004)	(0.003)	(0.002)
High-Treat 2017-18	0.007	0.008**	0.003	0.002
	(0.006)	(0.004)	(0.003)	(0.002)
Low-Treat 2018-19	0.005	0.006	0.005*	0.000
	(0.006)	(0.005)	(0.003)	(0.001)
High-Treat 2018-19	0.003	0.008**	0.004	-0.001
	(0.005)	(0.004)	(0.004)	(0.002)
Low-Treat 2020-21	0.009	0.010*	0.005**	0.002
	(0.006)	(0.005)	(0.002)	(0.002)
High-Treat 2020-21	0.006	0.008*	0.003	0.000
	(0.005)	(0.004)	(0.003)	(0.003)
Observations	408	408	395	408
R^2	0.882	0.809	0.734	0.802
District FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
age cohort	YES	YES	YES	YES
educ categories	YES	YES	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

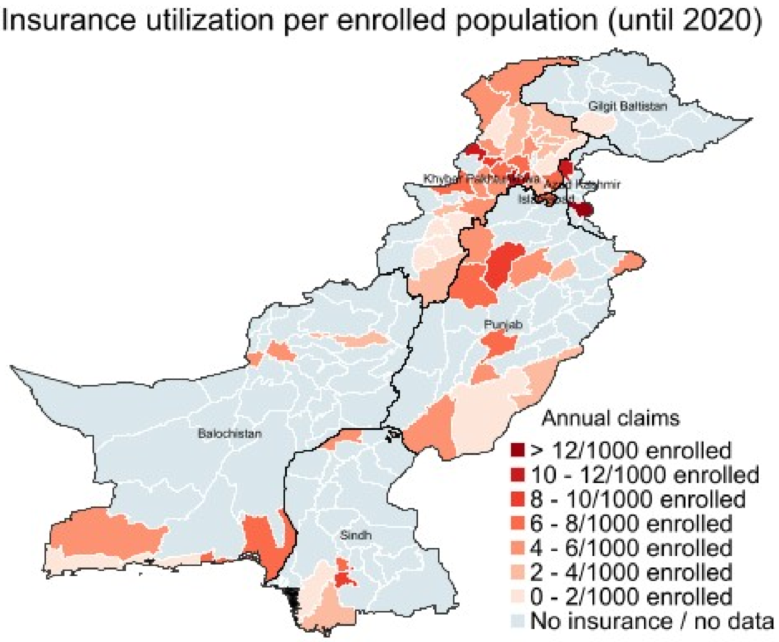
B Balancing tables & Maps

Table B.1: Balancing table for pre-treat period 2014-15

	(1)		(2)		(3)	
	mean	sd	mean	sd	b	t
international migration	0.004	0.004	0.005	0.007	-0.002***	(-4.098)
inter-district migration	0.072	0.035	0.073	0.034	-0.001	(-0.190)
migration from rural	0.044	0.029	0.047	0.028	-0.005	(-1.575)
migration from urban	0.028	0.017	0.026	0.017	0.005***	(3.007)
migration in last 4 years	0.217	0.076	0.246	0.079	-0.043***	(-4.213)
labor force participation	0.322	0.050	0.307	0.091	0.033***	(5.193)
age	22.930	1.772	22.293	1.719	0.615***	(3.250)
young-cohort	0.748	0.030	0.759	0.033	-0.015***	(-4.154)
productive-cohort	0.176	0.021	0.166	0.024	0.025	(0.777)
old-cohort	0.076	0.020	0.075	0.019	-0.000	(-0.233)
primarty education	0.604	0.096	0.652	0.059	-0.024***	(-3.141)
secondary education	0.222	0.088	0.176	0.057	0.026***	(3.573)
higher education	0.040	0.030	0.029	0.013	0.003	(0.472)
female	0.492	0.018	0.494	0.023	-0.010***	(-4.424)
Observations	47		41		454	

Table B.2: Balancing table for pre-treat period 2013-14

	(1)		(2)		(3)	
	mean	sd	mean	sd	b	t
international migration	0.003	0.003	0.004	0.006	-0.002***	(-4.098)
inter-district migration	0.077	0.036	0.071	0.033	-0.001	(-0.190)
migration from rural	0.046	0.029	0.045	0.025	-0.005	(-1.575)
migration from urban	0.031	0.017	0.025	0.020	0.005***	(3.007)
migration in last 4 years	0.209	0.067	0.241	0.083	-0.043***	(-4.213)
labor force participation	0.316	0.050	0.304	0.088	0.033***	(5.193)
age	22.886	1.818	22.148	1.649	0.615***	(3.250)
young-cohort	0.750	0.029	0.763	0.031	-0.015***	(-4.154)
productive-cohort	0.173	0.020	0.162	0.025	0.025	(0.777)
old-cohort	0.077	0.020	0.076	0.018	-0.000	(-0.233)
primarty education	0.611	0.100	0.663	0.057	-0.024***	(-3.141)
secondary education	0.216	0.095	0.164	0.055	0.026***	(3.573)
higher education	0.037	0.028	0.026	0.015	0.003	(0.472)
female	0.490	0.018	0.498	0.026	-0.010***	(-4.424)
Observations	47		40		454	



Note: *The provided map depicts insurance utilization per 1000 enrolled individuals. Beginning with the minimum value of 2 per 1000 people, the utilization remains notably low in these particular districts, even for the enrolled population. The highest observed insurance utilization per 1000 people is 12, signifying that, out of every 1000 individuals enrolled, only 12 actively utilize the insurance coverage..*

Figure B.1: Utilization by enrolled population