Restrict or Let Them Go? The Impact of Raising the Minimum Working Age on Education and Labor Market Outcomes.

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Abstract

The change in the minimum age of 14 to 15 for participation in the labor market has a greater and immediate impact that redirected significant children of 14 years of age to stay in school for one more year. The policy change structure gives us a rare opportunity to estimate the causal impact of return to education using the classic difference-in-difference methodology instead of relying on a relatively weak instrument. In the first stage, I find that an increase in the minimum working age helps in increase school enrollment, decrease labor force participation, and reduce income for the age of 15. In the second stage, it helps individuals complete high school, college degrees, and technical diplomas, enabling them to move into better job sectors. In the heterogeneous analysis, I find that most of the variation comes from rural areas, which was expected. In the gender-based analysis, I observe a greater impact on females in terms of enrollment and completion of high school and college degrees, mainly through the reduction of early child marriage.

[0]I am really thankful to my supervisors, Prasad Bhattacharya, Senior Lecturer at Deakin University, Umair Khalil, Senior Lecturer at Deakin University, and Romain Gauriot, Associate Lecturer at Deakin University, for their guidance and suggestions throughout the study period. In addition to my supervisory team, I am really thankful to Sascha Becker, Professor at Monash University, James Kung, Professor at Melbourne University. Furthermore, I presented this paper in Deakin University in 2023 and in Australian Econometric Society 2024, Adelaide University and received worthy suggestions from different people, I really thankful to all those.

1 Introduction

Majority of the developing countries in the world has minimum working age to protect the children from the early entry into the labor market, yet little is known about the effect of these laws on education attainment and labor market outcomes ILO (2018).[1] This paper exploits an unusual natural experiment to estimate the impact of increasing the minimum working age in Pakistan. The experiment arises from a government policy change in 2016 that increased the minimum working age in one province, while all the other provinces retained the exiting minimum working age. In Pakistan, prior to 2016, the minimum working age was 14 years across all provinces, contravening ILO regulations. However, in 2016, the government of Punjab raised the minimum working age to 15 years, while other provinces—Khyber Pakhtunkhwa, Balochistan, and Sindh—maintained the 14-year minimum.

The literature on the impact of increasing the minimum working age on educational and labor market outcomes is limited and presents mixed findings. Studies conducted in United Kingdom, Mexico, Malawi, Colombia, and Brazil provide new insights into the relationship between this policy change and its effects on student enrollment, educational outcomes, earnings, and crime Oreopoulos (2006); Piza and Souza (2014); Oppong-Nkrumah et al. (2019); Bargain and Boutin (2021); Huttunen et al. (2023). Most of these studies suggest that raising the minimum working age increases time spent in school and reduces work participation. However, when examining gender and regional differences, the findings remain inconclusive. Apart from this, these studies have very limited control group to ensure the robustness of the results. In most of these studies, the analysis relies only on time dimension which commonly know as before-and-after approach. In this situation, we cannot identify an internal control group, which may weaken the analysis. In a before-and-after analysis, national trend or time-related factors may influence the results.

This paper contributes to the existing literature in four distinct ways. First, it provides a robust and comprehensive research design for difference-in-difference analysis, widely regarded as one of the most reliable causal techniques. By exploiting the both time and geographic variations, provides the deeper insight and strengthen the ability to isolate the true impact of policy change. Second, by conducting a gender-based analysis, I identify the primary beneficiaries of this policy change. In the context of gender discrimination, women often suffer Marco-Gracia and Beltrán Tapia (2021).[2]. However, when the government increases the minimum working age, it helps women stay in school longer, primarily due to a reduction in early child marriage, as females are more frequently victims of this outdated tradition compared to their male counterparts. Overall, school enrollment increases by 9.8%. When comparing by gender, females show a higher increase in school enrollment at 10.6%, compared to 9.2% for males. Labor force participation decreases by 4.8%, with this variation coming solely from males, as females are less involved in labor market, particularly in urban areas Bank (2018); PBS, 1996. Although female participation in the labor market shows a reduction, it is not statistically significant.

Third, this study exploits regional variation to identify the primary beneficiaries between urban and rural areas as the policy change can have varied impacts in different

[1] Child labor remains a persistent issue worldwide, despite extensive efforts to eradicate it. According to the 2020 report by the International Labor Organization (ILO) and UNICEF, approximately 160 million children (97 million boys and 63 million girls) are engaged in child labor, and nearly half are involved in hazardous work. Globally, 1 in 10 children participates in the labor market and is exposed to hazardous conditions ILO (2020). In Pakistan, around 9.4% of children (11.2% of boys and 7.7% of girls) are engaged in the labor market PES (4 15).

[2] Marco-Gracia and Beltrán Tapia (2021), explaining gender discrimination in detail, they highlight that discriminatory practices lead to gender-specific mortality, particularly among children aged 1 to 5. This study claims that parents prioritize males over their female counterparts during infancy and childhood. However, this process can be observed throughout a person's life.

region Wu et al. (2006). Previously, few studies explored this dimension but failed to produce solid findings. However, this study goes one step further by also examining the gender impact within this regional analysis and provides conclusive results. The impact of increasing the minimum working age is slightly higher for children living in rural areas, as most school-age children in urban areas are already enrolled in school. In urban areas, school enrollment increases by 9.1%, which is slightly lower compared to rural areas, where it is 10.7%. A similar pattern is observed in employment, where the reduction in employment is slightly higher in rural areas 5.1% compared to urban areas 4.5%. In gender comparison, I get an interesting result that is truly representative of what is happening in the country. In urban areas, males show slightly higher enrollment compared to females, as most school-age females are already enrolled in school WB (2023). In contrast, rural areas show a greater impact on the female side, as more school-age males are enrolled in school compared to their female counterparts. The reason for this opposite situation is the gender disparity between rural and urban areas. In urban areas, parents generally give equal preference to both genders in terms of education, whereas in rural areas, more preference is given to male children. However, some parents in urban areas who cannot afford the standard of urban living might send their male child to work to overcome hunger issues. That is why, when the government changes policies to restrict this, the impact is more visible on the male side, whereas the opposite is true in rural areas.

However, when comparing between urban and rural settings, we observe that women living in rural areas benefit more. The reason is that gender discrimination is more prevalent in rural areas, where parents often prioritize sending their male children to school, believing it will provide financial returns in the future when they are unable to work ASER (2011)[3]. Due to this outdated tradition, early child marriage is more common among rural which predominantly affects girls UNICEF (2016); Modak (2019). Previously, school enrollment was higher for boys and lower for girls PBS (2015). By raising the minimum working age, the policy helps girls stay in school longer and delays early child marriage. The incidence of early child marriage among 15–18-year-olds decreases by 1.3%, with nearly all of the reduction coming from rural areas, where it stands at 2.3%. In gender comparison, the decline in early child marriage is more pronounced for females than males, as it is a more common issue for girls. However, when analyzing regional differences, there is no significant reduction for either males or females in urban areas, whereas a significant decline is observed in rural areas, with females experiencing the larger reduction. Due to this mechanism, female enrollment in rural areas increases more, by 12.8%, compared to urban females, where it stands at 7.8%.

Fourth, this might be the first study to go a step further by examining the completion of relevant degrees, and employment transitions across different sectors. For this purpose, I included all age groups exposed to the policy change since 2020. Children who were 12-15 years old in 2016 would have been exposed to the policy change and would have made decisions regarding their completion in the treated group. Therefore, for high school completion, we consider individuals aged 16–19 years, while for a college degree, we consider those aged 17–19 years as the treated group based on the 2020 PSLM. We compare this treated group with the same cohort in 2014, both in the treated and control provinces, while also considering the rest of the provinces in 2020. I find no overall change in high school completion; however, in the heterogeneous analysis, high school completion increases by 6.2% only in rural areas. In the gender-based analysis, I find a positive and significant impact in all cases, but only for females. However, in college degree completion,

[3]In urban areas, there is less gender discrimination compared to rural areas. Children in rural areas have a 32% lower likelihood of attending school and a 50% higher likelihood of not being educated compared to those in urban areas. However, when examining gender disparities in education, rural males are 19.5% less likely to attend school, while rural females face a 47% lower likelihood of attendance ASER (2011).

I find a positive overall impact (1.7%). In the heterogeneous analysis, I find a positive and significant impact (3%) only in rural areas. In the gender-based analysis, the variation observed in the overall results is primarily due to women. However, in the regional-based gender analysis, the impact is insignificant in urban areas, whereas in rural areas, both men and women show improvement in college degree completion, and women outperform their male counterparts. This aligns with the first-stage results. However, in the case of employment and sectoral transition, I do not see any significant improvement, as most of these individuals are still in school, which can be seen in Appendix Table 7. Most studies explain that we might not see the impact in the short run, as the treated group stays in school beyond the minimum age. However, in the long run, a clear difference between the treated and control groups may emerge once the treated group completes their schooling and enters the labor market Angrist and Krueger (1991); Oreopoulos (2006).

Apart from all these contributions, the most important contribution is in the context of developing countries, particularly in the case of Pakistan. Since the government increased the minimum working age, no study has analyzed the impact of this crucial policy change on enrollment and other relevant outcomes. Whenever a policy changes, empirical evidence is essential to inform the government about its impact and to acknowledge its efforts, which can serve as motivation. If the policy shows a positive impact, the government can extend it to other provinces and vice versa. This study may be the first to establish the causal impact of this policy change, helping the government understand its effects and consider extending it to the remaining provinces.

In the existing literature, the effects of raising the minimum working age vary among students of different backgrounds. On the one hand, increasing the minimum working age can increase earnings, as spending more time at school allows students to obtain a better education Baland and Robinson (2000). Individuals who enter the labor market with higher educational levels are more likely to secure formal employment opportunities and earn higher wages, contributing to the long-term well-being of their families Angrist and Krueger (1991); Oreopoulos (2006). However, students from disadvantaged backgrounds may suffer due to the ban on child labor. In impoverished areas, raising the minimum working age and extending mandatory schooling by one or two years may not be effective, as these children often play a crucial role in their families' financial stability. For families relying on their children's income, it is necessary to keep their children working to prevent hunger in the household Basu (1999).

In literature, the primary reason identified for relying on the income generated through child labor is poverty. Due to impoverished conditions, parents often choose to send their children to the labor market, choosing a trade-off between education and child labor Baland and Robinson (2000); Jafarey and Lahiri (2002). Hence, if these students drop out of school due to financial difficulties and seek employment, they may not secure formal jobs. Consequently, they might be compelled to work in the informal sector, exposing them to exploitation and jeopardizing their health and future earnings as adults. Consequently, such families may face ongoing struggles to meet their basic needs throughout their lives.[4]

[4]To study more deeply why increase in the minimum working age can put negative effect on economically deprived people we can see these study: Basu (1999); Horowitz and Wang (2004). These studies briefly explain the Cause, consequences, and cure of the child labor. These studies explain that why child labor remains in the labor market. they Put light on different dimension of child labor and explain the child labor traps. If we wanted to see how increase in the minimum working age works in the developed countries prospects we can explore studies: Manacorda (2006); Rey Canteli et al. (2018). Rey Canteli et al. (2018) discuss about the increase in the minimum working age in Spain. This study found that increase in the minimum working age increase post compulsory and non-compulsory among the individuals who turned 14 after the reforms. Because of increase in the education, it also affects the labor market in positive way. However, there is different impact of reforms on male and female.Manacorda (2006), explains the child labor supply and labor supply of the other households. It focuses on the variation in the legal minimum working age in 1920 in United state and result indicate that if a child enter into the labor market his/her siblings more likely to enter into the school.

School attendance and educational attainment is negatively affected by participating in the labor market Khanam and Ross (2011). When students engage in labor market activities, there is a higher probability of dropout. Educational attainment decreases by approximately one year for every additional hour of paid work per week in the labor market Ray (2002). The increase in the minimum working age has a different association with gender and the short run and long run. Piza and Souza (2014), finds that the increase in the minimum working age has a positive impact on student enrolment But the earning is negatively related to this affected cohort in the long run. Huttunen et al. (2023), show that enrolment in any secondary school can reduce the chance of being committed in crime.

Increasing the legal minimum working age serves as a strategy to eradicate child labor from the labor market. However, its effectiveness relies on the uniform implementation of policies nationwide. Yet, solely raising the minimum working age may not reduce child labor, particularly in developing nations. Instead, it often results in the displacement of child labor from the formal to the informal sector. Consequently, the policy change may not yield significant reductions in child labor rates. Additionally, age alone explains only a minimal percentage of the variation in child labor participation or engagement in paid work within the labor market Edmonds and Shrestha (2012).[5] Why increase in the minimum working age is ineffective and shows a small variation in child labor? There can be the several reasons. One can be the government increases the minimum working age just because of the pressure of International Institution but do not have real intentions to reduce the child labor by increasing the minimum working age. Therefore, they do not bother about the implementation of the legal minimum working age Edmonds (2014).[6]

The rest of the paper is organized in the following way. Section 2 focuses on Institutional background and policy setting used in the analysis. Section 3 explains the data collection sources, descriptive analysis and summary statistics. Section 4 elaborates the econometric technique employed for empirical analysis. Section 5 presents the empirical findings. Section 7 represents the different robustness test to make sure that our results are causal. Section **??** Concludes the debate and provides some recommendations and the way forward.

2 Institutional Background

2.1 Child Labor and Reforms

Child labor is not only an issue in developing countries but also in developed ones. According to the International Labor Organization, 152 million children are engaged in child labor worldwide, with half of them working in hazardous conditions. Out of these 152 million, 88 million are boys and 64 million are girls. Although significant progress has been made in reducing child labor in the last two decades from 16.0% to 9.6% of children in the labor market, the rate of reduction slowed down during 2012-2016, with only a 1% decrease. This slowdown is not a significant progress in reducing child labor. In Africa, many countries have taken strong actions to reduce child labor, but it continues to increase. However, we are moving in the right direction, but we need to accelerate the process in order to achieve our objectives ILO (2018). The International Labor Organization is focusing on the issue of child labor under the program of Ending Child Labor by 2025. However, it states that if we continue at the same pace as we experienced between 2012 and 2016, we will still have 121 million children in child labor by 2025 ILO (2018).

[5] Edmonds and Shrestha (2012) Explains the relationship of increase in the minimum working age on child labor. As per the discussion of this paper, it is argued that the increase in the minimum working age has been central point of discussion among the policy makers for the last fifteen years. However, by taking 59 low-income countries it explains that age can only explains one percent variation in the child labor while 63 is determined from the household attributes.

[6] International Labor organization's convention 138 deals with the legal minimum working age while convention 182 deals with the worse form of child labor. But we have seen that the International labor organization failed to achieved these goals.

The Africa region is securing the first position in terms of child labor, where 19.6 percent of children are engaged in the labor market. Governments have implemented strong policies to eliminate child labor. However, broader economic, geographic, and geopolitical forces have acted against these policies, resulting in a slowdown during 2012-2016 due to less reduction in child labor in the Africa region ILO (2018). On the second position, Asia pacific region stands where 7.4% of the children engaged in the child labor ILO (2018). Various South Asian countries, including India, Pakistan, Bangladesh, Nepal, and Sri Lanka, have implemented significant policies to tackle the critical issue of child labor. However, a considerable number of children, around 16.7 million aged 5-17 years, are still engaged in the labor market, impacting their health, education, and overall development ILO (2015). If we specifically look at the child labor figures in the case of Pakistan, 13.7% children aged 10-17 years are being engaged in labor force ILO (7 18). Gender disparity is also prevalent in South Asian countries. In Pakistan, for instance, female school attendance aged 10-17 years is nearly 15% lower than their male counterparts. Furthermore, four South Asian countries, including Pakistan, Afghanistan, Bangladesh, and Nepal, have the highest gender disparities. Alarmingly, Pakistan ranks second in gender disparity, with a ratio of 82 females for every 100 males ILO (2015).

Pakistan has made different reforms and adopted different policies to eliminate the child labor from the labor force. Like the other member countries of International Labor Organization, Pakistan adopted Declaration of Fundamental Principle of Rights at work, 1998. This declaration deals with the four principles: freedom of association and right of collective bargaining, elimination of forced labor, and Child labor and discrimination. In 2000, the government started national policy and action plan to combat child labor. the purpose of this program is to eliminate the child labor from the exploited and hazardous work and rehabilitation of vulnerable child labor. The International Labor Organization's (ILO) Convention No. 182 deals with the worse form of child labor ratified by the Pakistan in 2001 ILO (1999). According to this there is Prohibition of all form of slavery, involvement of child in the armed conflict, sexual exploitation of child, working in a place which is harmful for safety and health. Furthermore, Pakistan also ratified in 2006 International Labor Organization's No. 138 which deals with the minimum working age. According to this who is under the age of 15 cannot enter the labor market but in a country where the education facilities are inadequate the minimum working age would be 14 years old.

In October 2008, Pakistan started Benazir Income Support Program (BISP). It was basically the poverty alleviation and women empowerment program. However, this program was also considered beneficial for the reduction in child labor. Churchill et al. (2021), found that there is no short run impact of BISP program on child labor in the short run while in medium and long run it causes the reduction in the child labor Churchill et al. (2021). In 2016, Punjab government under the Punjab Restriction on Employment of Children Act, 2016 defines that any child under the age of 15 cannot participate in the labor market. If the violation happens there will be a fine of 10,000 rupees to 50,000 rupees and punishment of no less than seven days and up to the six months. the penalty and punishment would be worse if children are involved in force labor, slavery. In this situation the fine will range from 200,000 rupees to 1 million rupees while the punishment will be no less than three years and up to seven years.

2.2 History of Minimum working age

After 1990, there has been a continued global trend towards raising the minimum working age and strengthening regulations to protect children from exploitation in the labor market. Many countries have introduced or revised laws to ensure that children have access to education and are not subjected to hazardous or exploitative work environments. For example, countries like India, Bangladesh, and Pakistan have implemented laws setting the minimum working age at 14 years, with restrictions on the types of work children can undertake and the number of hours they can work ILO (2017). Similarly,

in developed countries such as the United States and those in Europe, minimum working age regulations have been revised to align with changing social norms and economic conditions, with a focus on balancing the rights of young workers with the need for their protection. International efforts, led by organizations like the International Labor Organization (ILO), have also played a significant role in promoting global standards for minimum working ages and supporting countries in implementing and enforcing effective child labor laws. Out of the 187 member states of the International Labor Organization, 175 have ratified Convention No. 138, which addresses the elimination of child labor and mandates that member countries set the minimum working age at 15, prohibiting children from entering the labor market ILO (1973). Although this conviction has been ratified by many member States challenges remain in ensuring universal compliance with minimum working age regulations, particularly in informal sectors and regions with weak governance structures.

Despite the ratification of Convention No.138 by many member states, numerous countries have yet to establish the minimum working age at 15 years. However, there are a few countries that have increased the minimum working age, including Brazil, Mexico, Belgium, Austria, and some others that have aligned their standards with those of the International Labor Organization ILO (2017). In case of Pakistan, the Employment of Children Act, 1991 deals with the child labor. It defines that any person who is under the age of 14 is considered to be the child while if the person is between the age of 14 years and under 18 years of age is enlisted into the adult. The adult children cannot be employed in any work that is defined as hazardous for children expect participating in governmental associated training school and supporting family business.If anyone is found in the violation of these rules it would be punished by the imprisonment for up to one years, a penalty of 20,000 rupees, or both. Therefore, as per the Employment of Children Act 1991, the minimum working age in Pakistan was 14 years of old and no person can be admitted into the employment before completing the 14 years of age GOV (1991). However, before 2016, In Pakistan, the minimum working age for non-hazardous work was still 14 years for all provinces. However, In 2016, Punjab Province has increased minimum working age from 14 to 15 under the Punjab restriction on employment and children ordinance GOP (2016). Moreover, Islamabad territory which is regulated by the Federal government has also raised the minimum working age from 14 to 15 years old.

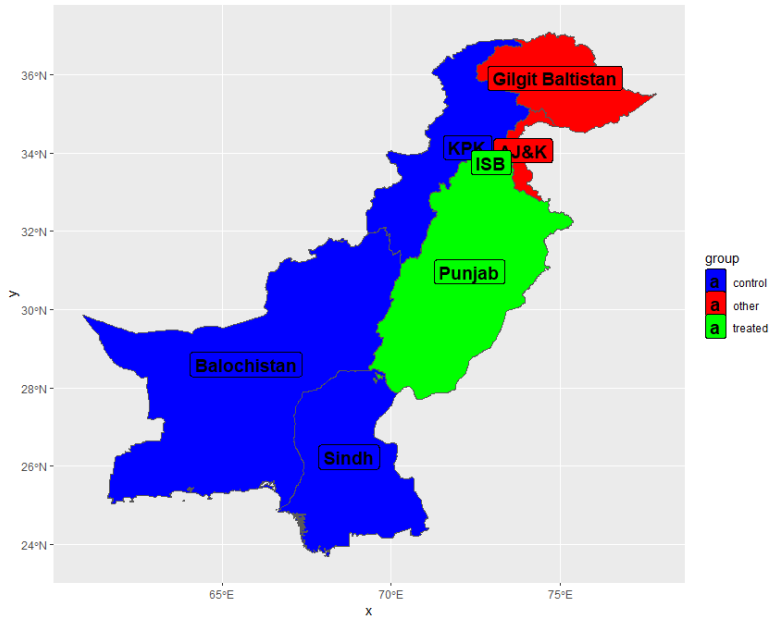


Figure 1: Treated vs Control

To better understand our study, we include a map of Pakistan in Figure 1. Pakistan has four provinces and two self-governing regions (Kashmir and Gilgit-Baltistan) under its administration. In the map, areas in green indicate regions where the government raises the minimum working age. All other colors areas maintain the previously set minimum working age. Thus, the green province (Punjab) represents our treated group, while the provinces with blue colors represent our control group. The red colors represents the self-governing areas (Kashmir and Gilgit-Baltistan), which are not included in the control group due to data availability limitations. Moreover, self-governing regions operate under different governing bodies with potentially distinct implementation structures. Including these areas in the control group could introduce bias to the results. Therefore, we narrow our control group to only include the provinces of Pakistan.

2.3 Implementation

2.3.1 Heterogeneous Effect

Every country comprises diverse demographic regions, each inhabited by individuals from distinct economic and social contexts. Comparing rural and urban areas, urban residents are generally more educated and better settled. This happens because people in cities can easily go to schools and learn from experienced teachers Bianchi et al. (2022). As a result, those living in cities have more chances to succeed and often do better than those in rural areas because they have better education.

Therefore, when the government makes any policy change, it often results in heterogeneous effects between regions and genders. This is because people in different regions adopt policy changes differently based on their educational backgrounds. For example, when China introduced the one-child policy, its effects varied between urban and rural areas Short and Fengying (1998). One of the important reasons for this varied effect can be the inequality in education that exists between urban and rural areas in China. People living in urban areas are typically more educated and have been exposed to higher-quality teachers compared to those in rural areas Bianchi et al. (2022). Therefore, less-educated individuals may not understand the purpose and consequences of policy changes as well as educated individuals do. Piza and Souza (2014) Basu (1999) these are other studies that explain how changes in labor market policy affect people differently based on their backgrounds.

However, a similar structure exists in Pakistan, where there are differences in terms of education and socioeconomic background between urban and rural areas. Apart from these differences there is also a difference in implementation in the urban and rural. If we consider gender disparity, Pakistan ranks second in South Asia ILO (2015). The responsibilities regarding child labor laws and implementation are divided between the Federal and Provincial Governments. The provincial governments of Pakistan are primarily responsible for implementing laws and policies related to child labor. This includes enforcing child labor laws, providing education and vocational training, and rehabilitating child laborers. However, the Federal Government of Pakistan also plays a crucial role in addressing child labor. The responsibilities of the Federal Government include formulating national policies, collecting data, and providing financial assistance to provincial governments to help them implement rules and regulations. Furthermore, Pakistan is a member of the International Labor Organization (ILO) and has ratified many ILO conventions associated with child labor. These conventions establish international standards for the protection of child labor. The Federal Government of Pakistan is responsible for ensuring that Pakistan complies with its obligations under these conventions.

When comparing urban and rural areas, it becomes evident that the living standard in urban areas is higher than in rural areas. This is attributed to greater earning opportunities available to people in urban settings ILO (2020). Additionally, in terms of education, the urban literacy rate is generally higher than that in rural areas. According 2019-20 Pakistan Social and Living Standard survey (PSLM), the Urban youth literacy

rate (15-24) is 84% while rural youth literacy rate (15-24) is 65% PBS (9 20). However, youth Literacy rate is higher in male with 79% than the female with 65% PBS (9 20). One key factor that distinguishes urban and rural areas is awareness. Urban residents tend to be more aware of policy changes due to their higher level of education and easy access to various modes of information, including print and electronic media. Therefore, based on these differences, we can expect to see varied results in terms of region and gender.

2.3.2 Practical Steps Towards Implementation

When the government increased the minimum working age in Punjab, it was in response to unfortunate events that occurred in the past few years. This demonstrates the true intention of the government to eliminate child labor from the market. For the implementation of child labor laws, a task force is established to assess the impact of these laws in Punjab. Then, based on the task force reports, the government establishes different policies to eliminate child labor Tribune (2018). Furthermore, another government that came into power with the majority in almost all province except Sindh decided to establish task force to eliminate the existing child labor Dawn (2020). The basic objective of these task forces was to raid different places to identify the existence of child labor and then inform the official authorities to take action. However, the Sindh government is also launching different mechanisms to restrict children under the age of fourteen from working and to encourage their attendance in school. For example, in 2017, the government cracked down on the existence of child labor in the market. Along with strict implementation of labor laws, the government also imposed a six-month imprisonment and a fine of 50,000 for those who violate the laws Reuters (2017).

The process of eliminating child labor began in 1994 and has been strengthening with each passing year. In 1994, the government signed a Memorandum of Understanding with ILO-IPEC, aiming to eliminate child labor. Under this memorandum, 50 action plans were initiated, including interventions in the soccer ball industry (Sialkot), street children (Peshawar), and the carpet manufacturing industry (Gujranwala, Lahore). According to estimates, around 25,000 children benefited from these initiatives. Second, in 2003, ILO-IPEC launched a four-year project to support an ongoing program called the Time-Bound Program (TBP) to combat child labor. As a result, approximately 11,800 children benefited by receiving vocational training and healthcare. In 2006, ILO-IPEC implemented another initiative, the Pakistan Earthquake Child Labor Response Project, targeting 2,500 children who were engaged in child labor before the project. Under this project, in 2010, 632 children received vocational training, and 3,626 children were enrolled in rehabilitation centers. Furthermore, before 2009, not all provinces had compulsory education law. However, even where such law existed, they were not often enforced. TO make the process of eliminating child labor more efficient, Government transferred legislation on labor matters to provinces under the 18^{th} Constitutional Amendment.

When labor matters are reserved with the provinces, it becomes an easier job as the duties are divided among the provinces. Before the 18^{th} Amendment, only the central government dealt with child labor issues. According to new provincial laws, two of four provinces (Punjab & KPK) increased the maximum amount of fines from PKR20,000 to PKR50,000 (Approximately US$190 to $475). Furthermore, according to Punjab Prohibition of Child Labour at Brick Kilns Act 2016 the amount of fines ranges PKR50,00 TO PKR500,00 (approximately $475 to $4,750). After when policy changed happened in Punjab, in July 2016, Committee on the Right of Child (CRC) was concerned about the less number of trained inspector, their involvement in corruption, and the lack of resources to inspect the places properly. It also investigated that the fines only not enough to be sufficiently effective. Therefore, this committee requested Government regarding the strengthen the capacity of the labor inspector.

Following the 18^{th} Constitutional Amendment, all provinces began establishing child labor laws and implementing them. This process started in 2015, when Khyber Pakhtunkhwa (KPK) enacted the KPK Prohibition of Employment of Children Act, 2015. Consequently, there was a noticeable increase in inspections and penalties from 2015 onwards. In 2016, Punjab introduced the Punjab Prohibition of Child Labor at Brick Kilns Act, 2016, and in 2017, Sindh enacted the Sindh Prohibition of Employment of Children Act, 2017. Figures 2 and 3 illustrate the trends in inspections and penalties at the national level, showing continuous improvement over the years. However, the most significant progress occurred in 2015, when provincial governments became more proactive in establishing and enforcing labor laws. After 2015, national-level data on inspections and penalties is unavailable, but provincial figures are available for some regions. However, apart from the Inspections, and penalties we can also see the improvement in convictions that can be seen from the graph 12 in apendex.

Under the Punjab Act, 2016, the Punjab government conducted 30,676 inspections, detecting 2,673 child labor violations. As a result, 25 establishments were sealed, and 1,199 individuals were arrested. In 2017, 3,367 inspections were carried out, leading to 23 convictions from 36 prosecutions, with fines totaling PKR 21,291. In 2018, 8,367 inspections were conducted, resulting in 95 convictions, with fines amounting to PKR 134,000. In 2019, 9,538 convictions were recorded, with fines reaching PKR 0.56 million across 254 cases. In 2020, Balochistan conducted 69 child labor inspections and identified six violations. Of these, three cases resulted in fines, totaling PKR 14,000.

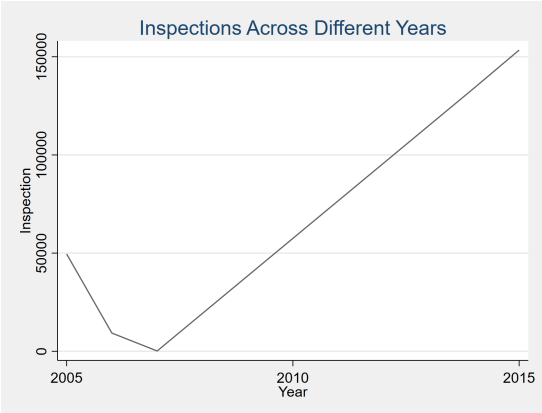


Figure 2: Inspections

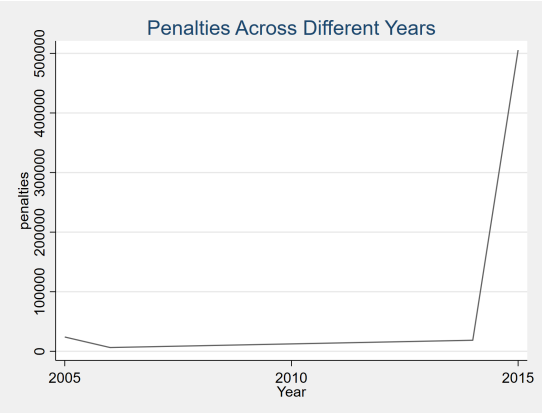


Figure 3: Penalties

Figure 4: Inspection and Penalties Across Different Years From ILO Data Source

Apart from these efforts, Pakistan has implemented various policies and mechanisms to ensure a significant reduction in the prevalence of child labor in the market. The government has established District Vigilance Committees, Labor Courts, and Child Protection Units. District vigilance committees consist of civil society members, lawyers, media personnel, and local government officials who inform the district magistrate about the existence of child labor. Meanwhile, Labor Courts decide on punishments for violations of laws, while Child Protection Units take children into custody, especially those rescued from exploitative labor situations DOL (2019). With a complete implementation structure in place, on one side, it would be very risky for employers to hire child labor. On the other side, it would also be risky for children to participate in the market while being part of an illegal labor force. Therefore, the majority of employers avoid hiring child labor, while the majority of parents are unwilling to send their children into the labor market because of the exploitative nature of the work.

3 DATA

We utilized data from the Pakistan Social and Living Standards Measurement (PSLM), the country's largest continuous survey, conducted by the Pakistan Bureau of Statistics

(PBS).[7] The Pakistan Social and Living Standards Measurement (PSLM) survey is a nationally representative household survey conducted annually by the Pakistan Bureau of Statistics (PBS). It covers the four provinces of Pakistan, as well as Islamabad Capital Territory. The survey started in 2004 as a PSDP-funded project and was later renamed PSLM in 2015. The second-to-last available round of the PSLM survey is from 2014-2015, which we'll refer to as the 2014 wave. This wave, conducted at both provincial and district levels, covered 80,000 households, with interviews taking place from late 2014 to early 2015. The most recent round of PSLM, conducted in 2019-2020, represents a significant expansion of the survey, with interviews carried out primarily in 2020. This 2020 wave included 195,000 households, more than double the number from the 2014 wave.

During the survey, it is recognized that some household members may not be available due to education or work commitments. In such cases, a designated main informant, typically a family member, is identified to provide information on behalf of absent members, including children. However, if other family members aged 12 or older are present during the interview, they are individually interviewed to provide their own information.

The PSLM survey offers detailed information on various indicators such as income, education, employment, health, and consumption. Concerning income, the dataset provides information on both monthly and annual income. Regarding education, the dataset indicates whether an individual is currently attending school. If the person is in school, the dataset specifies the current class of study. If the person is not in school, the dataset provides information on the reason for not being in school. Furthermore, this dataset provides information on the completed years of education. Regarding employment, the data indicates whether the person is currently working. This information allows us to compare trends in employment before and after the policy change.

We study the impact of policy reform on enrollment and completion. However, in data, there are some individuals who never attended school. For the main analysis, I drop these individuals from the data as there is nothing to do with them. If I carry these individuals in our sample, it might challenge the credibility of results. However, in our robustness section, I use the full sample by incorporating these individuals in sample size. For the completion of high school, I restrict the data to only 16 to 19-year-old individuals as most of the people starts this degree with age of 15 and finish it with the age of 16. However, there are the few exception cases who finish it with the age of 15 but we

3.1 Outcomes Variable

In the first stage, we have three outcome variables: school enrollment, employment, and log income. Here, enrollment and employment are represented as dummy variables, which are equal to 1 if the child is in school or the labor market, and 0 otherwise. The third outcome variable is income, which is essentially the monthly salary that individuals report at the time of the survey. To enhance interpretability, we take the natural logarithm of the monthly income.

In the second step, we use the completion of the $10th$ grade as the outcome variable to assess the impact of the policy on $10th$ grade completion. The completion rate is also represented by dummy variables, with a value of 1 indicating a person holding a Matric completion certificate, and 0 otherwise. Furthermore, we also examine sectoral transitions

[7] https://www.pbs.gov.pk/The Pakistan Bureau of Statistics (PBS) is the national statistical organization responsible for collecting, analyzing, and disseminating official statistics in Pakistan. Established to provide accurate and reliable data, the PBS plays a crucial role in supporting evidence-based decision-making and policy formulation across various sectors. The bureau conducts censuses and surveys, covering economic, social, and demographic aspects of the country, contributing to a comprehensive understanding of Pakistan's development landscape. With a commitment to transparency and data integrity, the PBS serves as a vital resource for researchers, policymakers, and the public. As far as the timing of every upcoming wave, There is no fixed schedule for collecting new data wave; sometimes is collected annually, and sometimes it can take 4 to 5 years to collect new dataset. Before 2015, the project was known as the PSDP-funded project, which started in 2004.

in terms of employment. For this purpose, we consider the share of employment in the agricultural, industrial, and services sectors in the total labor force by generating dummy variables. For example, if we want to calculate the share of agricultural employment in the total labor force, we assign a value of 1 to individuals working in the agriculture sector and 0 to those working elsewhere. However, someone may raise the question of how we can identify whether a person is working in a specific sector. The answer is that we identify individuals by using the unique code assigned to each part of a sector. For instance, the agriculture sector is divided into around 29 sub-sectors, each with its own distinct identity code.

3.2 Control Variables

In the balances test, we observe slight differences in mean values between the control and treated groups, particularly in the demographic section. Literature reveals many studies encountering similar situations, such as Bianchi et al. (2022), who suggest that these differences, although significant, may not substantially affect our analysis. To address this, we use father income and education as control variables as these are the most important determinants of of child education. Furthermore, this study employs fixed effects and control for these disparities. However, our study also identifies significant differences in some cases. To mitigate this, we introduce time fixed effects to neutralize temporal effects and province fixed effects to account for geographical disparities noted in the balance test.

4 Identification Strategy

Before 2016, children in Punjab and all other provinces could work at the age of 15. However, after 2016, children in Punjab were prohibited from working at the age of 15 due to an increase in the minimum working age, while in all other provinces, children could still work. To estimate the impact of child labor policy reforms, I employ the Triple Difference-in-Difference (DDD) approach by exploiting variations across time, geographic regions, and age cohorts. Specially, we compare 15-year-olds and 16-year-olds within the treated province in 2020, while also comparing them with their counterparts (15 and 16-year-olds) in the control province in 2020. To account for pre-policy differences, we also compare them with the 2014 cohort, where all individuals were in control regions before the policy change. This approach helps isolate the policy's effect by accounting for differences across time, regions, and age groups. For robustness purposes, I use different control groups. First, I restrict the analysis to only two waves: 2014 (pre-policy) and 2020 (post-policy), where I can ensure balance between the treated and control groups and apply the same Triple Difference-in-Differences (DDD) approach. Second, I conduct a before-and-after analysis solely for Punjab using a double Difference-in-Differences approach. Third, I limit the analysis to the 2020 wave and apply the standard DiD approach.

Treatment Group: The treatment group consists of individuals who are 15 years of age in Punjab in 2020. This age group is directly affected by the policy change. Before the reforms, children under the age of 15 could participate in the labor market in Punjab, but now they cannot. Consequently, individuals with the age of 15 in Punjab in 2020 are considered the treated group.

Control Group: In our control group, individuals who were 15 and 16 years old in all four provinces in 2014, 15 and 16 years old in all three provinces except the treated province in 2020, and 16-year-olds from the treated province in 2020 are considered part of the control group.

To investigate the impact of child labor reforms, this study utilizes rich data from five waves of the PSLM survey, spanning from 2007 to 2020. Before the reforms, I use four waves, while only one wave (2020) is available after the policy change. I can conduct an analysis using just two waves: 2014 and 2020. However, to enhance robustness, I incorporate all available data. For robustness checks, I can restrict the analysis to one wave before the policy change (2015) and one wave after the policy change (2020).

For empirical analysis, we estimate the following model for within-cohort-approach:

$$Y_{isp} = \alpha_0 + \beta(\text{Age15}_{isp} \times \text{Treat}_{isp}) + X'_{isp}\delta + \gamma_p + \sigma_s + \varepsilon_{isp}$$

In this context, Y_{isp} represents the outcome variables school enrolment, employment and log income and i represents the unit of observation for an individual in year s and province p. The dependent variable, denoted as enrolment which is school enrolment, employment, and income of 15 years old. The interaction term is a combination of two variables: age-15 representing individuals who are 15 years old in both the treated and control groups, and the treat variable, indicating whether the person is in the year 2020 and in the province of Punjab. If an individual is in Punjab and in the year 2020, the variable takes the value 1; otherwise, it is set to zero. We then multiply this treated group by the 'age-15' dummy to compare 15-year-old in the treated group with the control group. The α_0 represents the constant term while β captures the treatment effect on the 15-year-old cohort. The $X^{'}{}_{isp}$ represents the matrix of control variables where we are including the father's income and education to isolate the impact of policy change. The γ_p presents province level fixed effects. This term captures unobserved characteristics that are specific to each province but do not change over time. The basic purpose of this is to take into control all the other programs that are implemented over there and other differences among the provinces.

Furthermore, this study also includes the year fixed effects σ_s to capture the variations the occur over time. By incorporating year fixed effects, we control for the unobserved factors that are constant within year but vary across years. This ensures that our variables of interest are not confounding by overall time trend. When we look at the impact of policy change at the specific point helps us to isolate the impact of policy change on the outcome variables at specific time. The ϵ_{isp} is represented as error term in the model and standard error is clustered at district level. In our case, the next most important outcome variables that we want to estimate are the high school, college degree, and technical diploma completion. We argue that the province exposed to this increase in the minimum age policy would have a higher 10^{th} grade completion rate compared to unexposed provinces. Therefore, to empirically prove this, we estimate the following model using a within-cohort approach:

$$\text{Completion}_{isp} = \alpha_0 + \beta(\text{Age}_{isp} = \text{16-19} \times \text{Treat}_{isp}) + X'_{isp}\delta + \gamma_p + \sigma_s + \varepsilon_{isp}$$

The coefficient (β) represents the treatment effect of the policy change on outcome variable. The α_0 is represented as constant while γ_p represents province-level fixed effects.

$$\text{Employment_Share}_{isp} = \alpha_0 + \beta(\text{Age}_{isp} = \text{16-19} \times \text{Treat}_{isp}) + X'_{isp}\delta + \gamma_p + \sigma_s + \varepsilon_{isp}$$

In this equation, we aim to investigate the impact of the policy on the change in employment share within the total labor force across different sectors, including agriculture, services, and manufacturing. The variable Employment_Share is the dependent variable, representing the contribution of employment from i sector and p province to the total labor force. The coefficient β represents the treatment effect of the policy change on outcome variable. The α_0 is represented as constant while γ_p represents province-level fixed effects.

Difference-in-Differences is based on the assumption that the outcomes of the control and treated groups should follow similar trends, both in areas exposed to the policy change and in those that are not. In our case, the major concern is that the treated province was not selected randomly. Consequently, the post-reform changes in outcome variables might be the result of other unobserved factors, rather than the effect of the change in the minimum working age. Therefore, we address this issue in the next subsections 4.3 and 4.4, as well as all other potential threats to our identification.

4.1 Descriptive Analysis

We begin by illustrating the data graphically, focusing on enrolment and employment in both the control and treated groups. Figure 5 depicts the overall mean enrolment for each complete year of age. The graph displays two lines: blue line representing the mean enrolment for the year 2020 while red line representing the mean enrolment for the year 2014. This is essentially a comparison of mean enrolment before and after the policy change. However, in 2020, not all provinces experienced an increase in the minimum working age. We are considering the solid line as the treatment group, while the dashed line represents the control group. The rationale behind this choice is that when conducting a graphical analysis province-wise before and after the policy change, a noticeable difference in enrolment is observed primarily in the treated province. Therefore, the trend depicting increased enrolment in 2020 is essentially driven by the treated provinces. Moreover, Figure 6 and Figure 7 representing regional wise analysis.

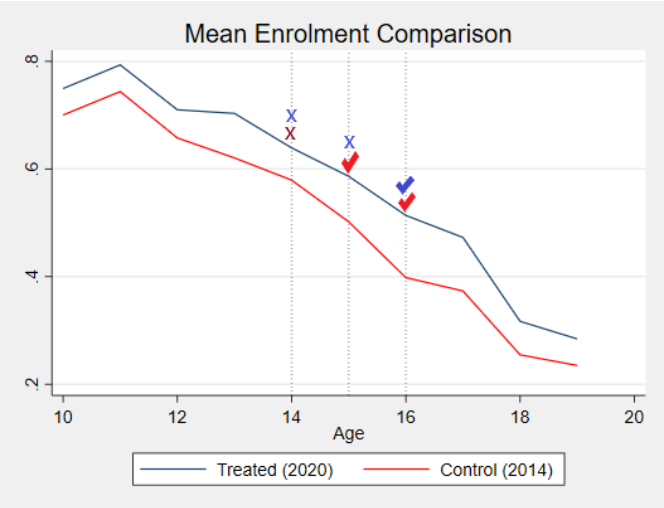


Figure 5: Enrollment Comparison Across Different Age Cohort

In Figure 5, Before the age of 14, we observe almost a similar trend in both the treatment and control groups. However, after the implementation of the ban on child labor, notable differences emerged. In the control group, there is a sharp decline in enrolment, indicated by a downward drop in the line. In contrast, the treated group exhibits a smoother decreasing trend. This comparison suggests that, following the imposition of the ban, the drop in enrolment at the age of 15 is less pronounced in the treated group compared to the control group. When we segment our graphical analysis into urban and rural cases represented in Figure 6 and Figure 7, a clear distinction emerges. In the urban area (treated), there is a smooth line from age 14 to 16, extending even to age 17. However, in the rural case (treated), there is a slight inward bend at the age of 16. Therefore, the rural effect we observe in Figure 6 is reflected in the overall analysis in Figure 7. This implies that the slight inward bend seen in the overall case primarily stems from rural areas.

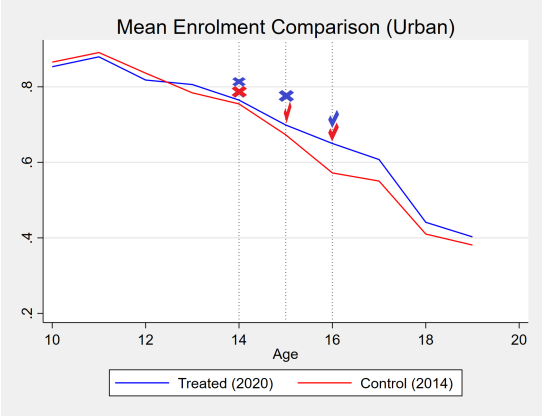


Figure 6: Urban

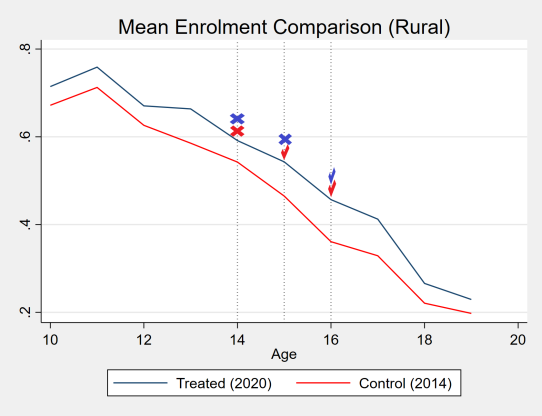


Figure 7: Rural

Figure 8: Urban and Rural Enrollment Comparison

Furthermore, if we make individual comparisons among 14 to 16-year-olds, we can observe some interesting outcomes. At the age of 14, individuals in both the treated and control groups are not legally permitted to work. Therefore, at this age, we do not see any significant differences between the treated and control groups in terms of trends. However, after age 14, while individuals in the treated group are still not allowed to work, those in the control group are permitted to start working after completing their 14th year. As a result, by the age of 15, we see a smooth decreasing trend in the treated group, whereas there is a sharp decline in the control group. Additionally, there is an interesting scenario when comparing the ages of 15 and 16. There is a sharper decline from age 15 to 16 compared to the decline from 14 to 15 in the control group, while the treated group shows a similar trend. The reason for this sharp decline might be due to the permission to work beginning at age 15.

Now it is clear that individuals over the age of 15 in the control group are allowed to work, while those in the treated group are not. However, at the age of 15, most people begin their Matric degree, which is a two-year program. Due to the work permission, some students in the control group might also be involved in job activities and not focus fully on their education. As a result, they may not perform well in the first year. This portion of the students might consider it better to leave school rather than potentially wasting another year, based on their performance in the first year. Therefore, we can see a sharper decline in school continuation after the age of 15. In contrast, children in the treated group, who are not allowed to work, can focus better on their studies during the first year of the two-year degree program. Performing well in the first year motivates them to continue to the second year and meet the minimum education requirement for participating in various opportunities.

4.2 Descriptive Statistics

Table 1 presents the summary statistics, divided into three parts: Overall, treated, and controlled. Columns 1 and 2 display the mean and standard deviation of the overall sample. Columns 3 and 4 provide the mean and standard deviation for the treated group, while columns 5 and 6 present the mean and standard deviation for the control group. Table 1 Panel A explores demographic factors, specifically comparing the educational levels, employment status, and income of fathers and mothers. The rationale behind including this section comes from our belief that Punjab is a prosperous province compared to other provinces, having a significant number of prime ministers and military officials. Consequently, parents in Punjab can have a higher level of education and employment, which may be the reason for higher enrollment in Punjab. However, our demographic analysis suggests that there is minimal disparity between the treated and control groups.

Panels B and C present educational and labor market outcomes. Panel B, Columns 4 and 6, show that school enrollment is higher in the treated group compared to the control group. Within the treated group, male and female enrollment rates are nearly equal,

while in the control group, males have slightly higher enrollment than females. Beyond enrollment, employment, another key outcome, is lower in the treated group than in the control group, as shown in Panel B, Columns 4 and 6. High school completion rates, also presented in Panel B, are higher in the treated group than in the control group. However, the overall gender-based analysis indicates that males, on average, have higher completion rates than females, as seen in Panel B, cocolumn. Interestingly, within the treated group, females have a slightly higher completion rate, whereas in the control group, males are more likely to complete high school.

Table 1: Summary Statistics

	Overall		**Treated**		**Control**	
	Mean (1)	Std. dev. (2)	Mean (3)	Std. dev. (4)	Mean (5)	Std. dev. (6)
			Panel A: Demographics			
Father: Primary education	0.146	0.353	0.162	0.368	0.146	0.353
Father: high School education	0.167	0.373	0.182	0.386	0.167	0.373
Father: college education	0.088	0.282	0.092	0.288	0.089	0.285
Father: Bachelor education	0.017	0.129	0.008	0.087	0.019	0.137
Father: university education	0.025	0.155	0.032	0.177	0.025	0.156
Mother: Primary education	0.098	0.298	0.150	0.357	0.092	0.288
Mother: high school education	0.064	0.245	0.11	0.315	0.059	0.236
Mother: college education	0.031	0.174	0.070	0.255	0.028	0.165
Mother: Bachelor education	0.004	0.063	0.007	0.086	0.004	0.061
Mother: university education	0.006	0.074	0.019	0.0138	0.005	0.68
Father Employment:	0.527	0.499	0.589	0.492	0.525	0.499
Father Log Income:	4.058	4.799	4.740	5.097	4.024	0.752
Mother Employment:	0.036	0.187	0.057	0.232	0.033	0.177
Mother Income:	0.231	1.442	0.319	1.729	0.215	1.384
			Panel B: Educational Outcomes			
Enrolment	0.686	0.464	0.767	0.423	O.680	0.466
Enrolment (M)	0.720	0.449	0.769	0.422	0.721	0.448
Enrolment (F)	0.636	0.481	0.766	0.424	0.616	0.486
completion10^{th}	0.082	0.274	0.089	0.285	0.075	0.263
completion10^{th} (M)	0.084	0.278	0.086	0.281	0.0832	0.275
completion10^{th} (F)	0.079	0.270	0.093	0.290	0.065	0.246
			Panel C: Labor Market Outcomes			
Employment	0.121	0.326	0.080	0.271	0.124	0.330
Employment (M)	0.177	0.381	0.121	0.326	0.179	0.383
Employment (F)	0.039	0.193	0.034	0.182	0.039	0.193
Log Income	0.526	2.041	0.347	1.733	0.528	2.029
Income (M)	0.802	2.248	0.598	2.248	0.788	2.449
Income (F)	0.121	0.963	0.065	0.751	0.125	0.969

Note: This table presents summary statistics. Panel A displays demographic variables, while Panels B and C represent educational and labor market outcomes, respectively. Columns 1 and 2 provide overall summary statistics. Columns 2 and 3 present summary statistics for those exposed to the policy change, while Columns 5 and 6 represent the group that has not been exposed to the policy change.

4.3 Differences Between Provinces

Part of our identification is to examine the differences between treated and control provinces. The structure of Pakistani politics is highly complicated, and it is nearly impossible for a single political party to secure a government with a 2/3 majority. Consequently, it is unlikely for the party in power at the federal level to legislate on labor laws for all provinces. This is because labor law legislation is a provincial matter, handled by the provincial government, and the federal government might not have control in all four provinces. Similar situation was in 2016 where Pakistan Muslim league was in power at federal level. In term of the provincial power, they only have the government in Punjab province. It is easy for the federal government to make a labor legislation in Punjab Province. Therefore, Federal government increase the minimum working age legislation

only in Punjab and Capital territory. There can be many reasons for the change in the minimum working age, one of which was the high incidence of child labor in Punjab. During the period of 2009-18, the highest number of child labor incidents were reported in Punjab. However, in the early months of 2016, some terrible incidents occurred that drew the government's attention to the need for reducing child labor ILO (2023).

In the province selection process, the government doesn't randomly choose provinces due to the absence of a majority in all provinces other than the province where the policy change occurred. However, a valid question could be raised about potential selection bias in the province selection process, which could impact the credibility of our results. When comparing the province where the policy change occurred (Punjab 2020) with other provinces, we observe that the treated provinces exhibit a more favorable trend in education, employment, and various other fields. In terms of education, the literacy rate is 61% in Punjab, where the government changed the minimum working age. In contrast, the rates are 56%, 53%, and 43% in Sindh, KPK, and Baluchistan, respectively, collectively forming the control group Rehman et al. (2015). To investigate this issue, we employ a balance test approach to examine the differences between the treated and control groups before the policy change occurred. For this analysis, we employ three waves of the Pakistan Social and Living Standards Measurement ($PSLM$) survey data, designating Punjab in 2014 as the treated group, while all other provinces in 2014 and earlier serve as the control group. Rather than relying on a simple t-test to examine mean differences, we adopt a fixed-effects approach to generate more reliable and robust results. The t-test is limited in that it cannot account for time-invariant factors and only captures differences in means, which may not provide a comprehensive picture. By employing the fixed-effects model, we are able to control for relevant confounding factors. Additionally, we perform a pretrend analysis to ensure the robustness of our findings and to validate the assumption of parallel trends, which is critical for causal inference.

Table 2 presents the baseline differences between the control and treated provinces. Columns 1 and 2 display the mean values for the treated and control groups, respectively, while column 3 reports the difference between the two groups. Here, I use the proper Difference-in-Difference approach with fixed effect, instead of using the traditional T-statistics approach to find out difference between mean values. The table is divided into three panels: Demographics, Educational outcomes, and Labor Market outcomes. In Panel A: Demographics, most variables do not show significant differences between the treated and control groups, indicating baseline similarity. However, some variables, such as father's logarithmic income, father's college education, father's bachelor's education, and mother's employment, show lower values for the treated group in two of the three cases. Panel B: Enrollment reveals negative and significant differences between the treated and control groups. In Panel C: Labor Market Outcomes, the treated group does not exhibit significant differences compared to the control group. These findings suggest that, at the beginning of the study, the treated and control groups are largely comparable, with no substantial advantage favoring the treated group in addition to the policy intervention. Second, where we observe the significant difference in all the cases treated group performing lower, except employment. However, we acknowledge the observed differences and account for these time-invariant and geographic variations in our analysis to ensure robust results.

However, there is the possibility that someone might raise a question about the method of province selection, as it was not random. The existence of this threat could call into question the reliability of our empirical results. To address this issue, in the first stage, we absorb geographic variations to ensure that preexisting characteristics are not the driving force behind the results. In the second stage, we only make a before-and-after comparison of the treated provinces in robustness, which mitigates these threats because now, almost all preexisting characteristics are the same. At this point, only two factors may contribute to the results: the policy change and the time effect. To address the time

Table 2: Baseline Mean Difference

	Treated	**Control**	**Difference**
	(1)	(2)	(3)
Outcome Variables	**Panel A: Demographic**		
Father: Employment	0.493	0.274	−0.051
Father: Log Income	2.752	1.879	−0.802**
Mother: Employment	0.240	0.078	0.016**
Mother: Log Income	0.414	0.197	0.005
Father: Primary Education	0.052	0.025	−0.010
Father: High School Education	0.074	0.050	−0.005
Father: College Education	0.041	0.047	−0.039***
Father: Bachelor Education	0.017	0.021	−0.019***
Father: University Education	0.003	0.002	−0.007**
Mother: Primary Education	0.046	0.022	0.003
Mother: High School Education	0.029	0.024	−0.013
Mother: College Education	0.034	0.021	−0.005
Mother: Bachelor Education	0.007	0.004	−0.001
Mother: University Education	0.001	0.000	−0.001
	Panel B: Educational Outcomes		
Enrollment	0.685	0.726	−0.053
Enrollment Male	0.685	0.726	−0.070**
Enrollment Female	0.685	0.726	−0.002
Completion (10th)	0.247	0.291	−0.002
Completion (10th) Male	0.247	0.291	0.019
Completion (10th) Female	0.247	0.291	−0.029
	Panel C: Labor Market Outcomes		
Employment	0.193	0.126	−0.007
Employment Male	0.193	0.126	−0.003
Employment Female	0.193	0.126	0.031

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. This table presents baseline differences between treated and control provinces. Panel A displays demographic variables, while Panels B and C represent educational and labor market outcomes, respectively. Columns 1 and 2 report the means for the treated and control groups, respectively. For enrollment and employment, we restrict the sample to 15- and 16-year-old, as any policy change would extend beyond this age range, which will be analyzed in the results section. Column 3 presents the results of the T-test. The findings are mixed—some differences are statistically significant, while others are not. However, the significant differences are relatively small in magnitude.

effect, we use the time fixed effect, which absorbs time variations, leaving us with the policy change.

4.4 Parallel Trend Assumption

In a Difference-in-Differences (DiD) analysis, a crucial assumption is the presence of parallel trends between the treated and control groups before the implementation of the policy change. This assumption posits that, prior to the policy change, the treated and control groups exhibit similar trends in the key outcome variables, namely Mean School Enrolment and Percentage of Employment. The parallel trend assumption asserts that any observed differences in outcomes are due to time-varying factors affecting both groups similarly. Specifically, it implies that Mean School Enrolment and Percentage of Employment would have followed comparable trajectories in the absence of the policy change. Any deviation from parallel trends after the policy change is attributed to the impact of the policy itself. This is fundamental for establishing a causal relationship between the policy intervention and the observed changes in outcomes.

Therefore, the parallel trend assumption necessitates careful examination of historical data to confirm that, before the policy change, both groups were on a similar trajectory. The actual divergence in trends should occur precisely at the point of policy implementation, reflecting the unique impact of the policy change on the treated group. This assumption ensures that any subsequent differences observed between the treated and control groups can be confidently attributed to the policy change rather than pre-existing divergences in trends. Verification of this parallel trend assumption is pivotal for the validity of the DiD analysis and the reliable identification of causal effects.

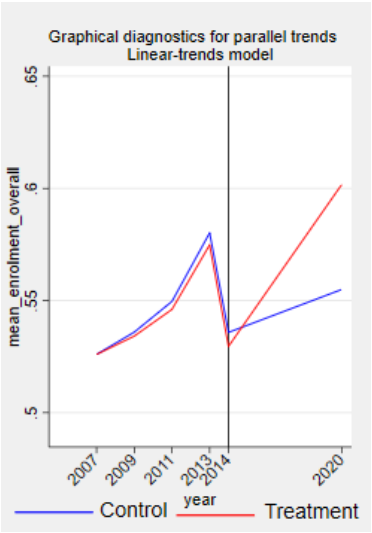


Figure 9: Enrollment

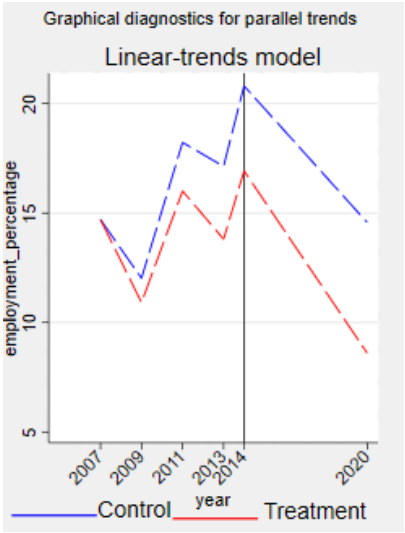


Figure 10: Employment

Figure 11: Parallel Trend Analysis Between Treated and Control

The figures 9 and 10 depict the pretrends in mean school enrollment and percentage of total employment across the entire dataset for 15-year-old cohort. The X-axis represents the years, spanning from 2007 to 2020. The policy change occurred in 2016 when the government raised the minimum working age. Consequently, the period before 2016 is considered the pre-policy time frame, while the period after 2016 is considered the post-policy change time frame. The dataset includes historical data before 2016, giving us plenty of information about trends before the policy change. However, we only have data for one year after the policy change, in 2020.

Both diagrams 9 and 10 exhibit consistent trends before the policy change. It is only after the policy change that a discernible difference in trends emerges between the treated and control groups. The figures effectively illustrate that, before the policy change, mean enrolment and percentage of total employment in the treated and control groups followed similar trends. The noticeable divergence in post trends emphasizes the impact of the

policy change on the outcome variables. This visual representation supports the assertion that the parallel trend assumption is satisfied in the pre-policy change period, reinforcing the credibility of the subsequent Difference-in-Differences analysis.

5 Empirical Findings

5.1 Overall

In this section, I begin discussing our main Difference-in-Differences (DiD) results, focusing on how the change in the minimum working age policy affects different outcome variables. In Table 3, we estimate equation 4 with difference-in-differences (DiD) analysis by using main control group. I break down our analysis into two parts: an overall perspective and a gender-based analysis, aiming to understand how the policy affects both men and women. The post-reform outcomes indicate an improvement in enrollment, with individuals showing reduced participation in the labor market. Before the reform, 15-year-olds were eligible to work. However, after reform, restrictions were imposed on individuals of this age group. Consequently, in 2020, the enrollment of 15-year-old increased, while their participation in employment declined. Examining Table 3 column 1, the results reveal a statistically significant 9.8% increase in enrollment. In parallel, employment decreased by 4.8%, and log income decreased by 30.1% compared to the control group. This shift toward spending more time in school and participating less in the labor market appears to contribute to better educational outcomes that we can see in the next section **??**. These findings are in line with previous evidence of the positive impact of increasing minimum working age on enrollment and the negative impact on labor force participation, as reported, for example, by Heymann et al. (2013); Piza and Portela Souza (2016); Kozhaya and Martinez Flores (2022). Dayıoğlu and Kırdar (2022), explain that an increase in the duration of schooling leads to higher enrollment and argue that enrollment and child labor are substitutes.

Table 3: Impact of policy change on different outcomes.

Outcome Variables	**Panel A: All**			**Panel B: Male**			**Panel C: Female**		
	Treat	**Mean**	**Treat**	**Treat**	**Mean**	**Treat**	**Treat**	**Mean**	**Treat**
School Enrolment	0.098***	0.545	0.104***	0.092***	0.629	0.100***	0.106***	0.446	0.113***
	(0.010)		(0.010)	(0.012)		(0.012)	(0.014)		(0.013)
Employment	−0.048***	0.156	−0.051***	−0.080***	0.227	−0.084***	−0.002	0.073	−0.003
	(0.007)		(0.006)	(0.009)		(0.009)	(0.006)		(0.006)
Log Income	−0.301***	0.522	−0.318***	−0.473***	0.856	−0.499***	−0.051***	0.131	−0.054***
	(0.027)		(0.027)	(0.045)		(0.045)	(0.016)		(0.016)
Covariates	✗		✓	✗		✓	✗		✓
Time Fixed Effect	✓		✓	✓		✓	✓		✓
District Fixed Effect	✓		✓	✓		✓	✓		✓
Observations	98,805		98,805	58,785		58,785	40,020		40,020

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. In this table, we estimate equation (1) where we examine the impact of an increase in the minimum working age on three different outcome variables: School Enrolment, Employment, and Log Income using a Triple Difference-in-Differences (DDD) approach. We conduct two types of analyses—overall and gender-wise. Panel A presents the overall results, while Panels B and C show analyses for males and females, respectively. All results indicate a significant causal impact of the policy change on outcome variables, except for female employment.

In gender-based comparisons, female school enrollment is higher than male enrollment. The policy change affects the treated age group differently, as shown in column 1. Male enrollment increases by 9.2%, while female enrollment rises even more, by 10.6%. Employment trends also differ. The treated male group sees a significant employment drop of 8.0%, while the treated female group experiences a much smaller, statistically

insignificant decrease of 0.2%. This difference may be due to lower female labor force participation, as reflected in their lower average employment levels (WB, 2018). Research, such as Oppong-Nkrumah et al. (2019), has shown that policy changes can have different effects on males and females, especially in low- and middle-income countries. In cases where school enrollment increases and labor market participation declines, incomes in the treated group tend to be lower. Our findings support this pattern, showing that the treated age group earns less than the control group. These results highlight the connection between education, employment, and income disparities in the studied regions. However, I observe slightly higher results when control variables are added to the regression, as shown in the third column of each analysis.

5.2 Heterogeneous Effect

Table 4 illustrates the impact of the policy change on school enrolment, employment, and log income by using the main treatment group. Panel A presents the overall urban results, while Panel B and Panel C represent the male and female outcomes, respectively. In Panel A, the urban results align with the overall case, with the primary distinction lying in the magnitude and in the female case which is represented in Panel C.

In urban areas, a significant proportion of school-age children are already enrolled, resulting in a comparatively smaller impact of the policy change, as reported by ASER, In rural area 32% students less likely to go to school and 50% more likely to be illiterate ASER (2011). [8] For instance, in Urban area, out of 100 percent, 80% of children are in school, and 20% are in the labor market. Within the 20%, 10% may comply with the regulations, and the remaining 10% may face challenges such as financial constraints or other family attributes, making them unable to abide by the law. Therefore, the increase in the minimum working age primarily affects the 10% of students who adhere to the rules. In contrast, rural areas may demonstrate a more substantial impact of the policy change in terms of magnitude due to a higher percentage of school-going children being out of school.

Table 4 Panel A, column 1, reveals an increase in school enrollment along with a reduction in employment and log income simultaneously in response to the policy change. Specifically, school enrollment increases by 9.1%, while employment and income decrease by 4.5% and 28.0%, respectively. Table 4 Panel B and Panel C represent the results of males and females in response to the policy change. There is also a positive and significant impact of the policy change on enrollment. However, in terms of employment and income, there is a negative and significant impact of the policy in panel B (Male), while it is insignificant in panel C (Female). Male enrollment increases at a higher rate compared to females, while the decrease in male employment exceeds that of females, suggesting alignment. In the urban part of the treated area, female enrollment is usually higher than male enrollment at age 15. The opposite is true in rural areas, where male enrollment exceeds that of their female counterparts (PSLM 2018-19). Therefore, when the government increases the minimum working age, we observe the opposite effect in terms of gender in the heterogeneous analysis. The impact would be on male enrollment in urban areas, as most females are already in school, while in rural areas, the impact would be on females, as most male children are already in school. This situation can be confirmed by Figure 16, which is in the appendix.

[8] Annual Status Education Enrolment (ASER) stands for the Annual Status of Education Report. It is an annual survey conducted in several countries to assess the status of education, particularly focusing on the quality of education. ASER is a significant initiative in the field of education research and plays several important roles.

Table 4: Impact of policy change on different outcomes in Urban area.

Outcome Variables	**Panel A: Urban**			**Panel B: Male**			**Panel C: Female**		
	Treat	**Mean**	**Treat**	**Treat**	**Mean**	**Treat**	**Treat**	**Mean**	**Treat**
School Enrolment	0.091***	0.679	0.096***	0.093***	0.697	0.104***	0.078***	0.659	0.078***
	(0.016)		(0.014)	(0.021)		(0.020)	(0.020)		(0.020)
Employment	−0.045***	0.089	−0.048***	−0.075***	0.146	−0.082***	−0.004	0.026	−0.004
	(0.008)		(0.008)	(0.013)		(0.012)	(0.006)		(0.006)
Log Income	−0.280***	0.573	−0.301***	−0.453***	0.979	−0.499***	−0.041	0.121	−0.042
	(0.051)		(0.048)	(0.089)		(0.082)	(0.030)		(0.031)
Covariates	✗		✓	✗		✓	✗		✓
Time Fixed Effect	✓		✓	✓		✓	✓		✓
District Fixed Effect	✓		✓	✓		✓	✓		✓
Observations	44,477		44,477	27,241		27,241	17,233		17,236

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. In this table, we estimate equation (1) where we look at the impact of an increase in the minimum working age on three different outcome variables: School Enrolment, Employment, and Log Income in the Urban area by Using Triple Difference in Difference (DDD). We conduct two types of analyses: overall Urban and gender-wise. Panel A shows the results for the overall Urban case, while Panels B and C represent analyses for males Urban and females Urban, respectively. All the results indicate a significant causal impact of policy change on outcome variables.

When we examine Panel C of Table 4, we observe that there is a significant impact of the policy change on enrollment, but insignificant impact on employment, and log income. There could be several reasons for the lack of significance in the impact of the policy change on employment and log income. First, females are less participated in the labor market. Therefore, we cannot see the significant reduction in the employment and log income. Second, according to the International Labor Organization (ILO) ILO (2020), rural areas tend to have a higher percentage of child labor. Therefore, when comparing women between urban and rural areas, it is important to note that most of the female child labor exists in rural areas and is associated with agricultural activities. However, there are fewer agricultural opportunities available in urban areas for women to participate in. This may contribute to the observed differences in log income between urban and rural areas.

The second sector where women are involved is the manufacturing sector. However, parents in urban areas are more aware of exploitation, especially sexual exploitation. Consequently, most parents avoid sending their female children to the labor market and seek alternative sources of income. For example, they may take on extra work themselves, as there are more opportunities available in urban areas, or they may send male children to the labor market instead. According to the International Labor Organization, only 1.50% of women in the urban area are involved in the labor market, while this figure is 9.60% in rural areas ILO (1996). Based on this percentage, we can conclude that fewer women are involved in the labor market in urban areas. Therefore, when the government increases the minimum working age, it affects enrollment because females are out of school, but not employment because not all women who are out of school participate in the labor market.

Table 5: Impact of policy change on different outcomes in Rural area.

Outcome Variables	**Panel A: Rural**			**Panel B: Male**			**Panel C: Female**		
	Treat	**Mean**	**Treat**	**Treat**	**Mean**	**Treat**	**Treat**	**Mean**	**Treat**
School Enrollment	0.107***	0.503	0.109***	0.095***	0.608	0.098***	0.128***	0.377	0.132***
	(0.011)		(0.010)	(0.013)		(0.012)	(0.014)		(0.014)
Employment	−0.051***	0.176	−0.051***	−0.084***	0.251	−0.085***	−0.005	0.088	−0.005
	(0.007)		(0.007)	(0.010)		(0.010)	(0.008)		(0.008)
Log Income	−0.370***	0.502	−0.321***	−0.501***	0.811	−0.505***	−0.068***	0.133	−0.070***
	(0.038)		(0.038)	(0.062)		(0.063)	(0.022)		(0.022)
Controls	✗		✓	✗		✓	✗		✓
Time Fixed Effect	✓		✓	✓		✓	✓		✓
District Fixed Effect	✓		✓	✓		✓	✓		✓
Observations	54,328		54,328	31,544		31,544	22,784		22,783

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. In this table, we estimate equation (1) where we look at the impact of an increase in the minimum working age on three different outcome variables: School Enrollment, Employment, and Log Income in the Rural area by Using Triple Difference in Difference (DDD). We conduct two types of analyses: overall Rural and gender-wise. Panel A shows the results for the overall Rural case, while Panels B and C represent analyses for males Rural and females Rural, respectively. All the results indicate a significant causal impact of policy change on outcome variables.

Table 5 presents the impact of policy changes on various outcome variables in rural areas, including school enrollment, employment, and log income. The findings are consistent with the overall results. However, when comparing urban and rural settings, the impact of the policy change appears to be more pronounced for both males and females in rural areas, as anticipated, given that a higher proportion of individuals in rural areas may be out of school. Apart of magnitude, the rural results align with those observed in urban areas, with the exception of female income, which shows a significant decrease. This divergence is attributed to differing patterns of female labor market participation: fewer females are involved in the labor market in urban areas, while participation is higher in rural areas. Consequently, when the government raises the minimum working age, it disproportionately affects female employment in rural areas, leading to a significant impact on their income levels. The Table 5 Panel A shows an increase in enrollment and a decrease in employment and log income in response to the policy change. However, when we examine Panels B and C, we observe that the increase in enrollment is higher for females compared to males, but there is a greater reduction in employment and income for males compared to females.

In the first stage, we observed a positive impact of the policy change on school enrollment, particularly for females. This raises an important question about what might happen in the next stage. If children stay in school longer, there is a higher probability that they will complete high school and college degrees compared to the control group. The effect may extend beyond college degrees, but not enough time has passed since the policy change to assess this. Therefore, we focus only on high school and college degree completion, as the treated age group consists of 16 to 19-year-olds based on the 2020 dataset. Table 6 presents the results of the second stage, which examines high school and college degree completion. This analysis is also divided by gender and region.

Table 6: Impact of Policy change on Completion

Outcome All	Panel A: All			Panel B: Urban			Panel C: Rural		
	Treat	Obs.	Mean	Treat	Obs.	Mean	Treat	Obs.	Mean
	10^{th} Grade Completion								
All	0.000	174,481	0.162	0.003	77,187	0.212	0.026***	97,294	0.145
	(0.018)			(0.021)			(0.021)		
Male	−0.047**	104,744	0.176	−0.060**	47,749	0.195	−0.017	56,995	0.169
	(0.017)			(0.028)			(0.021)		
Female	0.060***	69,737	0.058	0.093***	29,438	0.231	0.084***	40,299	0.117
	(0.023)			(0.025)			(0.024)		
	12^{th} Grade Completion								
All	0.017***	124,279	0.162	0.001	77,187	0.212	0.030***	22,123	0.145
	(0.007)			(0.013)			(0.007)		
Male	−0.002	75,160	0.176	−0.030	33,980	0.195	0.020**	13,097	0.169
	(0.008)			(0.016)			(0.010)		
Female	0.037***	49,119	0.058	0.034	20,560	0.231	0.044***	9,022	0.117
	(0.011)			(0.018)			(0.012)		
Covariates	✓			✓			✓		
District Fixed Effect	✓			✓			✓		
Year Fixed Effect	✓			✓			✓		
Age Fixed Effect	✓			✓			✓		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. In this table, we estimate Equation (2), examining the impact of an increase in the minimum working age on the completion of 10^{th} grade. We compare people who are 16 to 19 years old in 2020 in Punjab with those who are 16 to 19 years old in other provinces in 2020, as well as 16 to 19-year-olds in both treated and control groups in 2014. The results indicate a positive and significant impact in the treated group, especially for females.

In the first section, Table 6 explains the results of high school completion, divided by gender and region. Overall, Section 1, Column 2, shows that there is no significant impact of the policy change. However, when we break it down by gender, males show a negative impact, primarily from the urban area, while females show a positive impact. Previously, we observed that female enrollment was higher compared to their male counterparts in urban areas. When the government increased the minimum working age, males were the primary beneficiaries in the urban areas. After staying in school for an additional year, it is possible that these male students participated more actively in the labor market afterward, which could have impacted their completion rates. On one hand, there are more opportunities in the urban area where children can easily become involved in the labor market. On the other hand, the cost of living is higher in urban areas, and parents may not be able to sacrifice for another year, sending their children into the labor market to overcome financial issues. However, in terms of females, the results show that high school completion increased by 6.0%. In the regional-based analysis, there is no significant impact on urban high school completion, while in rural areas, high school completion increases by 2.6%. Furthermore, in the gender-based comparison, females show a positive and significant improvement in high school completion in both urban and rural areas. In urban areas, female high school completion increases by 9.3%, whereas in rural areas, it increases by 8.4%. In the first stage, we observed that females were the primary beneficiaries of the policy change in terms of enrollment. The same holds true for high school completion, as females show higher completion rates compared to their male counterparts. Several studies in the literature on the United States suggest that minimum school age laws help improve completion rates, including Angrist and Krueger

(1991); Oreopoulos (2006). However, I identified that females are the primary beneficiaries through the channel of reduced early child marriage, which helps them stay in school. When females have the opportunity to remain in school, there is a higher probability that most of them will complete their grade, as they tend to be more career-oriented compared to their male counterparts, who face more challenges in this regard because of involvement in other activities NBER (2007). Field and Ambrus (2008), show that each additional year of delayed marriage is associated with a 0.22% increase in schooling and a 5.6% increase in literacy rates. Furthermore, when the government imposes restrictions on school duration, it helps female students become less involved in daily household tasks, allowing them to complete their grades Dayıoğlu and Kırdar (2022).

However, after completion of high school and college degree, the next question that comes to someone mind is labor market outcomes as these people are now eligible for many skill level jobs after achieving the minimum hurdle that is high school completion. There are many studies in the literature explain that when we restrict children for one or two years more in the school it would impact the education and earring in the long run Angrist and Krueger (1991); Field et al. (2004); Oreopoulos (2006); Dayıoğlu and Kırdar (2022).

Table 7: All: Employment, Income, and Enrollment for All Exposed Children Aged 16–19.

Outcome Variables	**All**		**All**		**All**	
	Treat	**Obs.**	**Treat**	**Obs.**	**Treat**	**Obs.**
Panel A: Ever Attended School						
Employment	−0.062***	174,475				
	(0.019)					
Log Income			−0.337***	174,476		
			(0.087)			
Enrollment					0.060***	174,481
					(0.019)	
Panel B: Never Attended School						
Employment	−0.054*	121,838				
	(0.029)					
Log Income			−0.146	121,838		
			(0.135)			
Controls	✓		✓		✓	
Time Fixed Effect	✓		✓		✓	
District Fixed Effect	✓		✓		✓	
Age Fixed Effect	✓		✓		✓	

Note: *$p < 0.01$, $p < 0.05$, $p < 0.1$ represent significance at different p-values. In this analysis, we include all exposed individuals to assess the combined effect of the policy change on 16- to 19-year-olds. This study evaluates the impact of increasing the minimum working age on three outcomes: school enrollment, employment, and log income, using the Triple Difference-in-Difference (DDD) methodology. Panel A presents results for individuals who have ever attended school, while Panel B shows results for a control group consisting of individuals who have never attended school in their lifetime. The results indicate that the treated group is more likely to pursue higher education in subsequent years compared to both control groups, as reflected in higher enrollment rates and lower employment rates.

However, in our case, the policy change occurred in 2016, and I have only a single wave of data after this policy change—the 2020 PSLM survey. This means we have only four years to assess the impact of the policy change on the treated province. As discussed above, the average high school completion age is 16, but this does not mean that everyone completes high school at that age; it can extend to 17, 18, 19, or even 20. Another important consideration is that individuals who were required to stay in school

until age 15 are, in most cases, still enrolled. When analyzing the combined effect of the policy change on enrollment, employment, and log income for individuals aged 16 to 19, I found that these individuals continue to show higher enrollment compared to the control group.

Table 7 presents the empirical results. It shows that the treated group exhibits a 6% higher enrollment rate than the control group. Due to this higher enrollment, employment rates and log income for 16- to 19-year-olds in the treated group are lower compared to the control group. In Panel A, we include only individuals who have ever attended school, while in Panel B, we restrict the control group to those who have never attended school in their entire lives. Until 2020, employment rates remain lower for all exposed cohorts compared to both control groups—those who have ever attended school and those who have never attended school. However, in the long run, we expect higher employment rates for the treated group once these individuals leave school and enter the labor market.

Apart from overall employment, I was interested in conducting a disaggregated analysis to examine employment transitions across different sectors. Before the policy change, there were no significant differences in high school and college degree completion, as discussed in the robustness section. Given this, we do not expect any significant differences in employment transitions across sectors. However, after the policy change, we observe higher educational attainment, which suggests that individuals might transition to their desired sectors after meeting the minimum educational requirement. Nevertheless, as seen earlier, the treated group exhibits lower employment levels, and we do not yet observe significant employment transitions across sectors. In the long run, once these individuals leave school and enter the labor market, we expect to see such transitions. The basic idea is that the agricultural sector operates 24/7 but offers very low wages, while the industrial sector also involves physically demanding work. After meeting the minimum education requirement, rural individuals may transition from agriculture to the industrial or services sector, as both options are more viable. Urban individuals, who already have access to industrial jobs, may prefer moving into the services sector. However, at this stage, our empirical analysis does not provide evidence of these transitions.

6 Robustness

7 Robustness Tests

When conducting baseline difference analysis, as indicated in Table 2, significant differences were observed between the treated and control groups. This raises questions about the reliability of the results. To bolster the credibility of our findings, we employed an alternative control group to estimate the causal effect. All robustness checks are placed in appendix.

In the first robustness check, I conducted a temporal analysis of only the treated group, where Punjab 2020 serves as the treated group, while Punjab before 2016 is considered the control. This choice serves as an ideal control group, minimizing concerns about differences between the treated and control groups. The primary distinction lies in the temporal aspect, as I aim to account for time variations. This approach enhances the robustness of our results and ensures that any unobserved effects are less likely to be attributed to differences between the treatment and control groups. The results in Table 9 demonstrate the Difference-in-Difference analysis. In terms of direction and magnitude, the results are almost the same as those found in my baseline analysis. This check ensures the credibility of the results because mitigates concerns regarding differences between provinces, as we are only dealing with the treated province in a before-and-after analysis. In the second check, to address the potential endogeneity issue in more detail, we drop all the treated group districts that share a border with the control group. By doing so, we aim to mitigate the impact of external factors and address concerns related to endogeneity. Using the same econometric structure, the results in Table 11 support the main analysis, eliminating concerns that the results are driven by external factors.

In third check, I exclude Sindh from the control group. The reason for dropping Sindh

from the control group is that the province received support from USAID to implement the Sindh Basic Education Program, which focused on increasing children's enrollment and upgrading schools. The existence of this program in Sindh may affect enrollment in Punjab provinces. Second, this was a significant program, keeping this in the control group we might not find the true impact of policy change. Therefore, we excluded Sindh from the control group. However, I still observe almost similar results, as confirmed by Table 12. In the fourth check, we drop the time dimension from our analysis and focus solely on geographic variation. In this case, Punjab 2020 serves as the treated group, while the other three provinces act as the control group. This robustness check eliminates doubts that someone might raise regarding whether the results are driven by the time factor rather than the policy change. Table 10 confirms that the results are driven by the policy change rather than the time factor, as we still obtain the same results after dropping the time dimension.

In the fifth check, I examine the difference in enrollment and employment among 12 to 14-year-old children. The idea is that this age group is strictly prohibited from participating in the labor market, as all provinces set the minimum working age at 14, except Punjab, which increased it from 14 to 15. Therefore, there should not be any difference within this age group to confirm that the increase in enrollment, and decrease in employment and income among 15-year-old are due to the policy change. Table 13 shows a slight increase in enrollment in the treated province, primarily driven by females. However, there is no significant reduction in employment, and log income. Thus, the pattern observed here does not align with what we see in our main analysis. Second, this increase in enrollment is coming solely from urban females, a group that has already shown higher enrollment rates compared to their male counterparts. Therefore, when the policy change occurred, its impact was more pronounced among urban males than females, as most school-aged female children were already enrolled in school. However, in the policy change analysis, we observe most of the impact on urban males, as well as on both males and females in rural areas. In contrast, here, we do not see any significant impact in the rural case.

In the sixth check, I conduct a placebo test for high school and college degree completion. People who were 16 years old and above in 2016 were not exposed to the policy change, neither in the treated nor in the control group. Therefore, we expect no improvement in the treated province, as both groups—15-year-old individuals—were allowed to participate in the labor market. Here, we restrict the analysis to individuals who turned 15 after 2005, as the earthquake in Pakistan led to increased awareness and education levels due to interactions with international people and organizations. Including individuals who turned 15 before 2005 might introduce biases in our analysis. However, individuals who turned 15 in 2005 would be around 30 years old, while those who turned 15 in 2015 would be around 20 years old in the 2020 dataset. To ensure consistency, we restrict the data to individuals aged 20 to 30 and apply the same methodology as in our main analysis on educational attainment. The empirical results show no significant difference between the treated and control groups in terms of high school and college degree completion. Table 14 confirms that there is no major difference between the treated and control groups, except in high school degree completion, where the treated group under-performs compared to the control. This finding strengthens the robustness of our analysis, as it indicates that there is no significant difference apart from the overall case, where matric completion is lower in the treated group. It further highlights the effectiveness of the policy change, as before the policy change, matric completion was lower in the overall case, but after the policy change, there is an improvement.

In conclusion, our rigorous robustness checks, including various control group configurations, methodological adjustments, and placebo tests, consistently support the reliability of our baseline results. By conducting separate analyses for treated and control provinces, dropping border districts to mitigate external influences, and excluding

provinces with notable outcome improvements, we find that overall trends remain aligned with the initial findings. Additional tests, including excluding border districts, dropping the time dimension, and conducting a before-and-after analysis only for the treated group, confirm similar impacts, further affirming the robustness of the Difference-in-Differences analysis. Furthermore, removing Sindh Province from the control group, despite its improvements in Mean Enrollment and Percentage of Employment, does not alter the fundamental direction of the results. The consistent patterns in Enrollment, Employment, and log income reinforce the causal impact of the policy change. This comprehensive robustness assessment strengthens confidence in the validity of the observed effects.

References

Angrist, J. D. and Krueger, A. B. (1991). Does compulsory school attendance affect schooling and earnings? *The quarterly journal of economics*, 106(4):979–1014.

ASER (2011). Annual status of education report. Technical report, Pratham.

Baland, J.-M. and Robinson, J. A. (2000). Is child labor inefficient? *Journal of political economy*, 108(4):663–679.

Bank, W. (2018). Female labor force participation in pakistan: What do we know? Technical report, World Bank Group.

Bargain, O. and Boutin, D. (2021). Minimum age regulation and child labor: New evidence from brazil. *The World Bank Economic Review*, 35(1):234–260.

Basu, K. (1999). Child labor: cause, consequence, and cure, with remarks on international labor standards. *Journal of Economic literature*, 37(3):1083–1119.

Bianchi, N., Lu, Y., and Song, H. (2022). The effect of computer-assisted learning on students' long-term development. *Journal of Development Economics*, 158:102919.

Churchill, S. A., Iqbal, N., Nawaz, S., and Yew, S. L. (2021). Unconditional cash transfers, child labour and education: theory and evidence. *Journal of Economic Behavior & Organization*, 186:437–457.

Dawn (2020). Task force. Technical report, Dawn.

Dayıoğlu, M. and Kırdar, M. G. (2022). Keeping kids in school and out of work: Compulsory schooling and child labor in turkey. *Journal of Human Capital*, 16(4):526–555.

DOL (2019). Worse form of child labor. Technical report, US Department of Labor.

Edmonds, E. V. (2014). Does minimum age of employment regulation reduce child labor? *IZA World of Labor*.

Edmonds, E. V. and Shrestha, M. (2012). The impact of minimum age of employment regulation on child labor and schooling: Evidence from unicef mics countries. Technical report, National Bureau of Economic Research.

Field, E. and Ambrus, A. (2008). Early marriage, age of menarche, and female schooling attainment in bangladesh. *Journal of political Economy*, 116(5):881–930.

Field, E. et al. (2004). Consequences of early marriage for women in bangladesh. *draft, October,¡ efield@ latte. harvard. edu*.

GOP (2016). The punjab restriction on employment and children ordinance. Technical report, Government of Punjab.

GOV (1991). The employment of children act, 1991. Technical report, Government of Pakistan.

Heymann, J., Raub, A., and Cassola, A. (2013). Does prohibiting child labor increase secondary school enrolment? insights from a new global dataset. *International Journal of Educational Research*, 60:38–45.

Horowitz, A. W. and Wang, J. (2004). Favorite son? specialized child laborers and students in poor ldc households. *Journal of Development Economics*, 73(2):631–642.

Huttunen, K., Pekkarinen, T., Uusitalo, R., and Virtanen, H. (2023). Lost boys? secondary education and crime. *Journal of Public Economics*, 218:104804.

ILO (1973). Ilo conviction no. 138. Technical report, ILO.

ILO (1996). Summary results of child labor survey of pakistan. Technical report, International Labor Organization.

ILO (1999). Internation labour organization's convnetion no. 182. Technical report, ILO.

ILO (2015). Child labour in south asia. Technical report, International Labour Organization.

ILO (2017). Minimum working age in different countries. Technical report, ILO.

ILO (2017-18). The asia regional child labour project. Technical report, ILO.

ILO (2018). Conviction. Technical report, International Labour Organization.

ILO (2020). Child labour: Global estimates 2020, trends and the road forward. Technical report, International Labour Organization.

ILO (2023). Child labour in pakistan. Technical report, International Labour Organization.

Jafarey, S. and Lahiri, S. (2002). Will trade sanctions reduce child labour?: The role of credit markets. *Journal of Development Economics*, 68(1):137–156.

Khanam, R. and Ross, R. (2011). Is child work a deterrent to school attendance and school attainment? evidence from bangladesh. *International Journal of Social Economics*, 38(8):692–713.

Kozhaya, M. and Martinez Flores, F. (2022). Child labor bans, employment, and school attendance: Evidence from changes in the minimum working age.

Manacorda, M. (2006). Child labor and the labor supply of other household members: Evidence from 1920 america. *American Economic Review*, 96(5):1788–1801.

Marco-Gracia, F. J. and Beltrán Tapia, F. J. (2021). Son preference, gender discrimination, and missing girls in rural spain, 1750–1950. *Population and Development Review*, 47(3):665–689.

Modak, P. (2019). Determinants of girl-child marriage in high prevalence states in india. *Journal of International Women's Studies*, 20(7):374–394.

NBER (2007). Why do women outperform men in college? Technical report, NBER.

Oppong-Nkrumah, O., Kaufman, J. S., Heymann, J., Frank, J., and Nandi, A. (2019). The impact of increasing the minimum legal age for work on school attendance in low-and middle-income countries. *SSM-population health*, 8:100426.

Oreopoulos, P. (2006). Estimating average and local average treatment effects of education when compulsory schooling laws really matter. *American Economic Review*, 96(1):152–175.

PBS (2015). Pslm 2014-15 final report. Technical report, Pakistan Bureau of Statistics.

PBS (2019-20). Pslm survey. Technical report, PBS.

PES (2014-15). Population, employment and labour force. Technical report, Pakistan Economic Survey.

Piza, C. and Portela Souza, A. (2016). Short-and long-term effects of a child-labor ban. *World Bank Policy Research Working Paper*, (7796).

Piza, C. and Souza, P. (2014). Long-term efeccts of child labour bans on adult outcomes: Evidence from brazil. *University of Sussex, Sussex, UK*.

Ray, R. (2002). The determinants of child labour and child schooling in ghana. *Journal of African Economies*, 11(4):561–590.

Rehman, A., Jingdong, L., and Hussain, I. (2015). The province-wise literacy rate in pakistan and its impact on the economy. *Pacific Science Review B: Humanities and Social Sciences*, 1(3):140–144.

Reuters (2017). Crak down on child labor. Technical report, Reuters.

Rey Canteli, E. d., Jiménez-Martín, S., and Vall Castelló, J. (2018). Improving educational and labor outcomes through child labor regulation. *Economics of Education Review, 2018, vol. 66, num. October, p. 51-66*.

Short, S. E. and Fengying, Z. (1998). Looking locally at china's one-child policy. *Studies in family planning*, pages 373–387.

Tribune (2018). Task force. Technical report, Tribue.

UNICEF (2016). Child marriage in south asia. Technical report, United Nation Children Organization Fund.

WB (2023). Poverty. Technical report, World Bank.

Wu, X., Perloff, J. M., and Golan, A. (2006). Effects of government policies on urban and rural income inequality. *Review of Income and Wealth*, 52(2):213–235.

A First

A.1 Convictions Across Different Years

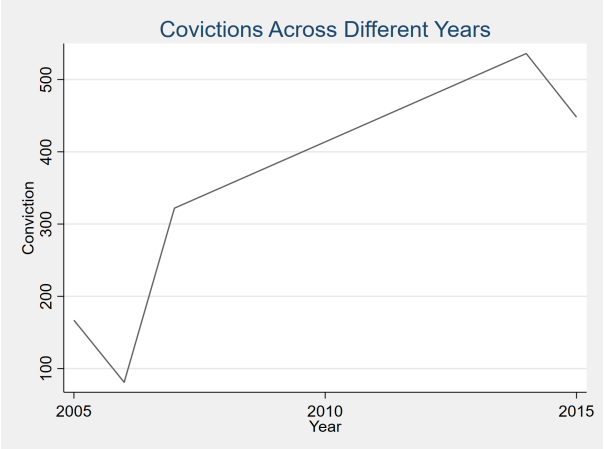


Figure 12: Convictions Across Different Years

Group	Male (Mean)	Female (Mean)	Difference
High School	0.086	0.093	-0.007
High School	0.083	0.065	0.018

Note: Here, I compare the sample mean of high school completion between genders within the treated and control groups to examine gender disparity in completion rates. The results show that gender disparity is lower in the treated group, whereas it is more pronounced in the control group. Interestingly, females lead in high school completion within the treated group, where the government implemented a policy change regarding the minimum working age. In contrast, males in the control group outperform females in terms of completion, and this gap may persist if the government does not intervene in a similar manner as it did in the Punjab case.

A.2 Gender Gap Reduction among Completion of High School

A.3 Migration

Group	Total	Born in Same District	Born in Another District
Migration All	20,053	19,554	499
Migration After 2016	-	-	129

Note: Here, I show how many people migrated from one province to another, particularly from Punjab to other provinces, after the minimum working age was increased. The total migration after 2016 is 129, with a smaller share coming from Punjab. However, even if we assume that all 129 migrants were aged 14 and 15 and migrated from Punjab to other provinces, it would still represent a relatively small and insignificant number of migrations.

A.4 Robustness

Table 8: Persistence effect of policy change on different outcomes.

Outcome Variables	**Panel A: All**		**Panel B: Male**		**Panel C: Female**	
	Treat	**Mean**	**Treat**	**Mean**	**Treat**	**Mean**
School Enrolment	0.091***	0.545	0.067***	0.629	0.123***	0.446
	(0.011)		(0.013)		(0.013)	
Employment	−0.040***	0.156	−0.055***	0.227	−0.002	0.073
	(0.008)		(0.011)		(0.006)	
Log Income	−0.206***	0.522	−0.275***	0.856	−0.000	0.131
	(0.045)		(0.073)		(0.025)	
Covariates	✓		✓		✓	
Time Fixed Effect	✓		✓		✓	
District Fixed Effect	✓		✓		✓	
Observations	89,504		53,384		36,118	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. In this table, we check the indirect impact of policy change on different outcomes variables. In treated part, children are restricted in school with the age of 15. However, this policy indirectly impact the 16 years old children as after staying in school with the age of 15 might force them to go one more year to complete Matric degree or go beyond. Here, we examine the impact of an increase in the minimum working age on three different outcome variables: School Enrolment, Employment, and Log Income using a Difference-in-Differences (DDD) approach. We conduct two types of analyses—overall and gender-wise. Panel A presents the overall results, while Panels B and C show analyses for males and females, respectively. All results indicate a significant causal impact of the policy change on outcome variables, except for female employment.

Table 9: Impact of policy change on different outcomes.

Overall: Punjab Vs Punjab						
Outcome Variables	**Treat**	**Mean**	**Treat**	**Mean**	**Treat**	**Mean**
School Enrolment	0.096***	0.677				
	(0.009)	(0.468)				
Employment			−0.046***	0.128		
			(0.005)	(0.334)		
Log Income					−0.332***	0.566
					(0.035)	(2.129)
Controls	✓		✓		✓	
District Fixed Effet	✓		✓		✓	
Year Fixed Effet	✓		✓		✓	
Observations	38,723		38,723		38,723	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. This table estimates $Y_{isp} = \alpha_0 + \beta(age_15 \times \text{Treat}_{s=2020,p=Punjab}) + \sigma_s + \epsilon_{isp}$, analyzing the causal impact of an increase in the minimum working age on three outcomes: School Enrolment, Employment, and Log Income. Using Difference-in-Difference (Single Difference), Punjab 2020 serves as the treated group, while Punjab before the policy change acts as the control group.

Table 10: Impact of policy change on different outcomes.

Overall: Only Geographic Variations						
Outcome Variables	**Treat**	**Mean**	**Treat**	**Mean**	**Treat**	**Mean**
School Enrolment	0.098***	0.677				
	(0.008)	(0.468)				
Employment			−0.048***	0.128		
			(0.005)	(0.334)		
Log Income					−0.337***	0.566
					(0.035)	(2.129)
Controls	✓		✓		✓	
District Fixed Effet	✓		✓		✓	
Year Fixed Effet	✓		✓		✓	
Observations	28,359		28,359		28,359	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. This table estimates $Y_{isp} = \alpha_0 + \beta(age_15 \times \text{Treat}_{s=2020,p=Punjab}) + \sigma_s + \epsilon_{isp}$, analyzing the causal impact of an increase in the minimum working age on three outcomes: School Enrolment, Employment, and Log Income. Here, we drop the time dimension and only focus on geographic variation. In this case, Punjab 2020 serves as the treated group, while all the other provinces in 2020 act as the control group.

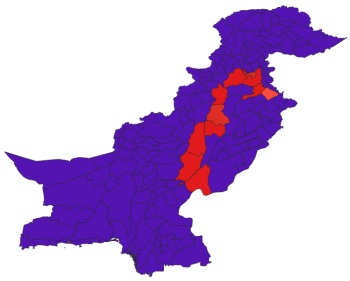


Figure 13: Drop Border Districts

Table 11: Impact of policy change on different outcomes.

Overall: Dropping Border Districts From Treated						
Outcome Variables	**Treat**	**Mean**	**Treat**	**Mean**	**Treat**	**Mean**
School Enrolment	0.094***	0.684				
	(0.012)	(0.465)				
Employment			−0.046***	0.122		
			(0.008)	(0.327)		
Log Income					−0.300***	0.566
					(0.528)	(2.043)
Controls	✓		✓		✓	
District Fixed Effet	✓		✓		✓	
Year Fixed Effet	✓		✓		✓	
Observations	95,431		95,431		95,431	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. This table estimates $Y_{isp} = \alpha_0 + \beta(age_15 \times \text{Treat}_{s=2020, p=Punjab}) + \gamma_p + \sigma_s + \epsilon_{isp}$. It evaluates the impact of an increase in the minimum working age on School Enrolment, Employment, and Log Income using Triple Difference-in-Difference (DDD). The analysis excludes border districts to ensure results are not driven by external forces from neighboring provinces.

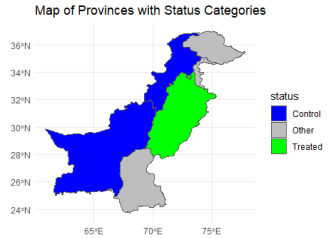


Figure 14: Drop Sindh Province

Table 12: Impact of policy change on different outcomes.

Overall: Dropping Sindh From Control						
Outcome Variables	**Treat**	**Mean**	**Treat**	**Mean**	**Treat**	**Mean**
School Enrolment	0.098***	0.684				
	(0.007)	(0.465)				
Employment			−0.045***	0.119		
			(0.004)	(0.324)		
Log Income					−0.324***	0.528
					(0.027)	(2.044)
Controls	✓		✓		✓	
District Fixed Effet	✓		✓		✓	
Year Fixed Effet	✓		✓		✓	
Observations	80,188		80,188		80,188	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. In this table, we estimate $Y_{isp} = \alpha_0 + \beta(age_15 \times \text{Treat}_{s=2020,p=Punjab}) + \gamma_p + \sigma_s + \epsilon_{isp}$. This analysis evaluates the impact of an increase in the minimum working age on three outcomes: School Enrolment, Employment, and Log Income using Triple Difference-in-Difference (DDD) methodology, excluding Sindh from the control group. Panel A presents overall results, while Panels B and C disaggregate the analysis for males and females, respectively. Results indicate a significant causal impact of policy changes on the outcomes.

Table 13: Placebo: Different Outcomes Comparison Between Middle School Chidren (12-14 Year Old).

Outcome Variables	**Panel A: All**		**Panel B: Male**		**Panel C: Female**	
	Treat	**Mean**	**Treat**	**Mean**	**Treat**	**Mean**
School Enrolment	0.031**	0.545	−0.002	0.629	0.095***	0.446
	(0.015)		(0.013)		(0.025)	
Employment	−0.014	0.156	−0.017	0.227	−0.002	0.073
	(0.007)		(0.010)		(0.005)	
Log Income	−0.022	0.522	−0.007	0.856	−0.003	0.131
	(0.023)		(0.037)		(0.012)	
Demographic Controls	✓		✓		✓	
Age Controls	✓		✓		✓	
Time Fixed Effect	✓		✓		✓	
District Fixed Effect	✓		✓		✓	
Observations	168,498		100,299		68,199	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. In this table, we make a placebo test between treated and control where we compare 12-14 years old in school enrollment, and other outcomes. We expect no difference since these children are restricted to stay in school in both treated and control. we used Difference-in-Difference approach to find out the empirical results. On the basis of this analysis, we can see that there is much significant difference between Punjab (treated) and other provinces (control).

Table 14: Placebo: Comparison of Matric and College Completion (20-30 Year Old).

Outcome Variables	**Panel A: All**		**Panel B: Urban**		**Panel C: Rural**	
	Treat	**Mean**	**Treat**	**Mean**	**Treat**	**Mean**
Matric Completion	−0.043**	0.545	−0.018	0.629	−0.029	0.446
	(0.019)		(0.019)		(0.023)	
College Completion	−0.007	0.156	0.016	0.227	−0.007	0.073
	(0.014)		(0.015)		(0.016)	
Time Fixed Effect	✓		✓		✓	
District Fixed Effect	✓		✓		✓	
Age Fixed Effect	✓		✓		✓	
Observations	308,533		135,291		173,242	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. In this table, we make a placebo test between treated and control where we compare 12-14 years old in school enrollment, and other outcomes. We expect no difference since these children are restricted to stay in school in both treated and control. we used Difference-in-Difference approach to find out the empirical results.

A.5 Child Marriage

Table 15: Impact of Policy Change on Child Marriage.

Outcome Variables	**Panel A: Overall**		**Panel B: Male**		**Panel C: Female**	
	Treat	**Obs.**	**Treat**	**Obs.**	**Treat**	**Obs.**
Overall	−0.013***	223,084	−0.006***	133,945	−0.024***	89,139
	(0.002)		(0.002)		(0.004)	
Urban	−0.000	99,017	−0.006	61,221	−0.000	37,795
	(0.003)		(0.003)		(0.006)	
Rural	−0.023***	124,067	−0.012***	72,724	−0.042***	51,343
	(0.002)		(0.002)		(0.004)	
Covariates	✓		✓		✓	
District Fixed Effect	✓		✓		✓	
Year Fixed Effect	✓		✓		✓	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represent significance at different p-values. This table estimates $Y_{isp} = \alpha_0 + \beta(Treat_{p=Punjab} \times \text{Age}_{=15-18}) + X'_{ip}\delta + \gamma_p + \epsilon_{isp}$. It examines the impact of an increase in the minimum working age on early child marriage using the Difference-in-Differences method. The treated group consists of individuals aged 15–18 in Punjab in 2020, while the control group includes individuals from other provinces in 2020 and all provinces, including Punjab, before 2016. The empirical findings show that an increase in the minimum working age has a significant impact on early child marriage, particularly for females in rural areas.

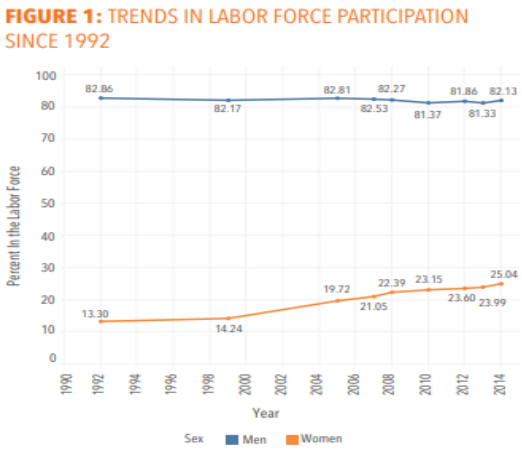
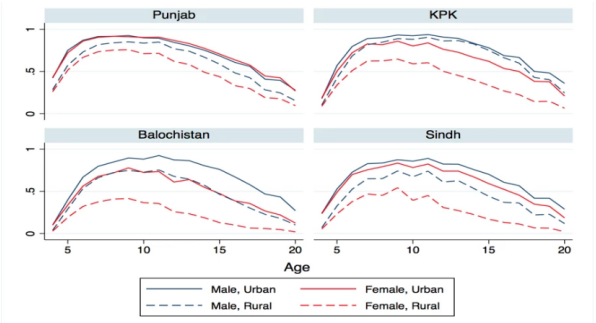


Figure 15: Labor Force Comparison Between Male and Female



Source: Author's calculations with data from the Pakistan Social Living Standards Surveys, 2018-19.

Figure 16: Enrollment Comparison Between the Gender and Region