THREE ESSAYS ON CAUSES AND CONSEQUENCES OF VIOLENCE AND CONFLICT

By

Abubakr Ayesh

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agriculture, Food & Resource Economics – Doctor of Philosophy

2022

ABSTRACT

THREE ESSAYS ON CAUSES AND CONSEQUENCES OF VIOLENCE AND CONFLICT

By

Abubakr Ayesh

This dissertation revolves around the theme of violence, crime and conflict. It is an attempt at (a) improving the understanding of the causes of violence and crime, and (b) the consequences of violence and conflict. Specifically, the first chapter investigates if air pollution can be a contributor to crime, the second chapter looks at the labor market impacts of terrorism in non-war zones, and the last chapter tries to understand the human capital accumulation decisions of permanently displaced individuals.

The first chapter looks at air pollution as a potential contributor to criminal activity. Using the seasonal variation in increase in air pollution –due to increased rice stubble burning– in the Punjab province of Pakistan, I explore the relationship between air pollution and crime. I combine eight different sources of data and use an instrumental variable approach to estimate the causal impact of air pollution on crime. Air pollution increases both violent and non-violent crimes, but the increase in violent crimes is much more salient. A one standard deviation increase in seasonal variation in air pollution increases violent crime by at least 15 percent. Back of the envelope calculations suggest that the cost of increased crime due to air pollution are at least 5 million US dollars, but maybe as high as 600 million US dollars. One potential mechanism driving the estimates is the reduction in earnings for middle aged male individuals due to high air pollution. The results suggest that the social costs of air pollution are much wider than those previously considered. They also have significant implications for developing countries whose economies rely on agriculture.

The second chapter of the dissertation looks at the impact of violence in non-war zones on incomes. A non-war zone does not have active presence of military, and it is not characterized by mass migration or shutting down of the economy. I use data from Pakistan on intermittent but sustained terrorist attacks for this purpose. After accounting for the intensity of the attacks, incomes

reduce by about 2.5 percent on average due to terrorist attacks. However, the effect is almost twice in the same month in which a terrorist attack takes place in a district. The effects are more severe for low skilled members of the labor force as well as for relatively inexperienced members. The two potential channels driving this impact are the changes in employment compositions across different occupations and a reduction in the number of days worked. From a policy perspective, relief and welfare efforts targeted towards (a) the most vulnerable groups in the labor force and (b) the sectors of the economy directly affected by the violence seem to be the best possible response -instead of general aid aimed at overall rebuilding of the economy which is more relevant for a war or conflict zone.

The last chapter considers the event of partition between India and Pakistan in 1947 that induced forced migration and permanent displacement of about 14.5 million people. I compare the educational outcomes of migrants and natives who were still in school going age when they were forced to migrate. I use a differences-in-differences approach. I also address the recent development in related literature on concerns related to identification, power, and bias in a differences-in-differences approach. I find that migrants are more likely to achieve certain educational milestones than their native counterparts. The results may be driven by the choices of older migrants pertaining to location and occupation. They also highlight the importance of an enabling and convenient environment for migrants which plays a crucial role in the pursuit of their educational goals.

This thesis is dedicated to the loving memory of my late grandmother. No other person would have been happier to see me cross this milestone.

ACKNOWLEDGEMENTS

I have always looked at each milestone in my life -material or otherwise- as a building block on a set of peers, mentors, and most importantly, privileges that I have possessed in my life. Ever since I read Malcolm X's autobiography, I try to remind myself of "Only the mistakes were mine" when it comes to looking at my accomplishments. From the day I made an appearance into this world till this moment as I write these sentences, there are numerous human beings and other factors that led to the completion of this dissertation. It will be impossible to mention everyone, and I will surely suffer from selection bias towards recent events in the following paragraphs.

To begin with, I must thank my major professor and my guidance committee members. Eduardo Nakasone, my major professor and my advisor, has provided me with thorough and quality feedback on all my work in the past four years. I started my PhD right after my undergraduate studies and lacked all the skills needed to conduct research. From programming in Stata to thinking about research questions and identification techniques, I have learnt enormously in the past 4 years. It has been a steep learning curve, particularly in the initial phase, but it's the process that has molded the raw researcher who was like clay into a polished ceramic in the form of a PhD 4 years later.

My second committee member, Scott Swinton, deserves a special mention because of the fantastic work relationship I have enjoyed with him. Just when I was about to quit my PhD owing to lack of direction and support, I found an incredible mentor in him. In the three years that I have known him, I have always felt free to knock on his door for advice on anything. I was lucky enough to take over Managerial Economics from him, as an instructor, because he was the perfect mentor for a budding teacher. Advice came in the form of recommendations for attending workshops, suggestions on preparing and presenting the class content, and being available to answer questions at any time. I also worked with him as a coauthor, and to his credit, he built my interest in a topic which is neither a part of my thesis nor was my subject of interest in my first two and a half years of the PhD. More importantly, the lessons I learnt while coworking on research were invaluable for a rookie. I learnt all about writing style, coordination with the research team, maintaining work flow and records, and research ethos. While this was my second research project overall, it helped me grow the most in terms of my evolution as a researcher and as an academic. I feel lucky to have had an amazing mentor in Scott Swinton these past years.

My two other guidance committee members have also helped me whenever I have asked. Songqing Jin has always been kind enough to review my work and provide feedback whenever I have asked him while Chris Ahlin helped me with developing the whole section on Conceptual Framework for my job market paper.

First and foremost, this dissertation belongs to my mother. As a single parent, she punched way above her weight to get me quality education and devoted a great amount of time to my personal and academic development outside of my school hours. Without those foundations, I would never possess the human capital required to enter a PhD program. Besides, from my everyday worries about the quality of food to my disillusion from the PhD when I almost decided to quit in my third year of PhD, she has patiently listened to all my tantrums. Next, my maternal grandparents played an equally important part, being a social support system that was a privilege to have, and whose importance I cannot underscore less.

I must also mention one of my high school mathematics teachers, Ahmad Tariq. I had lost interest in the subject as early as when I was 15. If it wasn't for him being my mathematics teacher for two consecutive years, I probably would have never taken a mathematics course in my undergraduate studies beyond the core requirements. Without a sound mathematical base, it would have been a miracle to get into any economics or related PhD program.

I must not forget the two professors who inculcated and nurtured my interest in research and academia during my undergraduate studies. Abid Aman Burki and Turab Hussain inculcated the passion for research in me through their teaching. Besides, they listened to my naive research ideas, refined my thought process, provided constructive feedback instead of dismissing me outright, and supported me through the process of my graduate school applications. Every instructor in my undergraduate studies had an important role to play but these two were instrumental in my decision to go for a PhD.

I have also been lucky that one of my best friends from undergrad also ended up in Philadelphia for graduate school. It has been a pleasure to occasionally visit Wahib Shah Ghazni in Philadelphia, and chat up research and life. It has been great support to have him here while I was away from family during my grad school.

One other person who entails a special mention is Rohit James. We met at an undergraduate conference in Khatmandu in 2017 and have always enjoyed discussing research since then, albeit virtually since he lives in India. I owe my third paper of the dissertation to him, because the idea came through my WhatsApp discussions with him, and he provided me with important sources of data for the paper.

This section will be incomplete without mentioning those without whom life in East Lansing would have been miserable. Fellow AFRE PhD student Salim Nuhu and I shared an apartment for almost three years. Besides helping me refine my raw research ideas, it was always fun to crack lame economics jokes, gossip about everyone in the department and vent after a tough meeting.

There are other fellow graduate students who deserve a special mention here. Danielle, Rahul, Salim, Hyunjung and Charuta were my first group of friends in the United States. I must also mention that I would have never passed the preliminary exams after the first year if it wasn't for this awesome study group. Other peers in my department whose company I have enjoyed throughout this journey include Aakanksha, Judhajit, Christine, Sudhir, Rubait, Sibbir, and Aaron, to name a few.

I specifically want to thank Danielle for dropping me home during the cold Michigan winter days, organizing and inviting us on dinners and Friendsgiving at her place, and road trips in Michigan in the summer of 2018. I will also admit that when I started my graduate studies, I was still living the undisciplined undergraduate lifestyle, and believed that a few all-nighters will help me pull off all my grad school deliverables. The first-year experience obviously put any such fantasies to rest but I took inspiration from Danielle's work ethics, planning and approach to grad school to build my work style, and it has been immensely helpful.

I must also mention two of my Pakistani friends, Faizan Shafique and Naveed Kamboh, who

have always inquired about me, even when I have failed to keep in touch. Faizan's spontaneous chai session invites are perhaps one of my best memories from East Lansing -though I might have troubled him with my coffee and green tea requests instead of his very famous Pakistani chaye that everyone loves. I have also been lucky enough to share good conversations and memories with Sara Tahir, Madiha Ghous, Azam Ali Sher, Zeeshan Riaz, and Hasan Fiaz.

Most importantly, East Lansing would have been unbearable without my "Desi Boys" group. We have shared a bond of friendship stronger than most I have observed in United States, and we truly have had each other's back, particularly in the last two years. Ankit, Siddharth, Bharath, Hitesh, Abhiroop, Yash, Sai and Vishal have been the social support system in East Lansing these past few years. I have always looked forward to our Friday night hang outs which are my perfect place to unwind. From needing a ride from the airport to accompanying one of us to the urgent care center, from taking care of each other as some of us fell ill with covid to food trips to Grand Rapids and Dearborn, and from cracking lame jokes to venting out about everything going on in our personal and professional lives, I could not have asked for a more supportive, candid, and fun group of friends. I will miss the bad movie nights, the board games, and solving the "where to dine" question once every week.

I must also not forget some of my friends in Columbus. Osama Sajid has been a mentor, friend, and someone to look up to ever since my sophomore year in undergrad. Visiting him, Adnan Mehmood and Rabail Chandio in Columbus every year in Christmas break has meant that I did not feel homesick when everyone went to spend time with their families. Osama was instrumental in teaching me R, helping me with air pollution and climate data for my job market paper, and offering advice on all things personal and professional. Our road trips in Michigan and California, and our time spent together in undergraduate holds a special place in my memories.

In this regard, I must not forget my friends from high school and undergraduate days whose company has been a privilege, and time spent with them has shaped me into the person I am today. Since the last 12 years, I have always looked forward to intellectual and philosophical discussions on life and this world with Saad Malik. Asad Jamil and Meera Omar were my study buddies in

undergraduate days, and I would not have understood many mathematical concepts without Meera's help. I have also hung out a lot with Asad Jamil, Hassaan Shaikh, Osama Shahid and Anas Zahid, and I have missed that time throughout my 5 years in East Lansing. The late night food expeditions, "khokha" chillings and fun endeavors are moments where I grew into the person I am today. Asad Shoaib, Ghania Shuaib and Abdullah Mashood are folks with whom I catch up once in a while but it always seems as if we just talked yesterday. Every one of these people have had a lasting impact on my life which will stay with me.

I must also make a thanks to AFRE's administration, in particular, Ashleigh Booth and Nancy Creed who made many complicated procedures seemingly easy for me. I must also not forget the current Chair for Graduate Studies, Nicole Mason-Wardell, who was kind enough to lend me her gown on the commencement, but more importantly, has been a source of immense support with a lot of administrative issues.

There are other groups that have been a part of my social circle in East Lansing. The East Lansing Islamic Center has played an important role in my social life, particularly during the month of Ramadan. I have enjoyed the Eid gatherings, the Ramadan Iftar scenes and meeting Muslim community members from all over the world. Additionally, I have been a part of various soccer and cricket communities in East Lansing, playing a competitive tournament occasionally, and that has been a great opportunity to have life outside of the grind that is graduate school.

There are many others who deserve a mention here, but I fear this section has already grown beyond its intended limit. I thank everyone who has been a constant support in my life and in my grad school journey.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

BURNED AGRICULTURAL BIOMASS, AIR POLLUTION AND CRIME

1.1 Introduction

Air pollution is known to have adverse effects on human life. It can affect both adult and infant health outcomes, such as mortality, lung cancer and heart diseases (Schlenker and Walker 2016; Currie and Walker 2011; Foster et al. 2009; He et al. 2020; Beatty and Shimshack 2014; AQLI 2019). Air pollution decreases productivity and reduces labor market participation (Hanna and Oliva 2015; Zivin and Neidell 2012), affects cognitive performances by inducing more mistakes (Lavy et al. 2014; Stafford 2014; Archsmith et al. 2018; Wangyang et al. 2021; Zivin and Neidell 2009), and induces people to make sub-optimal economic decisions in order to avoid exposure to pollution -known as avoidance behavior (Ito and Zhang 2020; Moretti and Neidell 2011; Zivin and Neidell 2009). The WHO estimates that ambient pollution accounts for about 4.2 million deaths worldwide. These economic costs are particularly high for developing countries since they do not have enough resources to support affected individuals in the form of remedial policies [1]. Furthermore, recent evidence suggests that the social costs associated with air pollution are much wider than commonly considered (Bondy et al. 2019; Herrnstadt et al. 2020).

In developing countries, reducing the social costs of air pollution to optimal levels is a complicated policy issue because, while the carbon emissions are likely to be low, the ambient pollution is likely to be very high [2]. Furthermore, developing countries are often characterized by highly inefficient institutions and weak law enforcement capacity. Developing countries lack in both the design and the implementation of basic policy frameworks that can help bring these kind of exter-

[1] These can include public health insurance or cash transfer programs which are very popular in developing countries.

[2] Ambient air quality is the outdoor air quality measured at the ground level, away from the direct sources of pollution. Ambient pollution can be higher in developing countries because they are less likely to invest in cleaner fuel sources and put necessary limits on regulations pertaining to energy, automobile and other sectors of the industry. This leads to high air pollution in the environment.

nalities to optimal levels [3]. This inability to efficiently implement environmental regulations can make it even more difficult to ensure that socially optimal levels of ambient pollution are produced.

Environmental degradation is often associated with industrialization. However, one form of anthropogenic pollution that does not come from the manufacturing sector involves fires in the agricultural sector. Farmers use fires to clear land and dispose crop residues. (Andrea 1991). In recent years, agricultural fires intended to clear crop residues account for roughly half of the burned biomass in forest fires (FAO 2018). While these fires have been extensively studied in the literature, their socioeconomic costs tothe society are still not well understood.

Can burned agricultural biomass intended to clear stubble drive up air pollution which can lead to an increase crime? In this paper, I consider crime as a social cost of air pollution, and by extension the social costs of the agricultural sector for the society at large. I examine the impact of air pollution on crime by exploiting the seasonal variation in rice stubble burning in the Punjab province of Pakistan. I use wind direction from major rice growing districts as an instrument, assuming upwind districts will be exposed more to air pollution than downwind districts. I combine about 8 different sources of longitudinal and cross-sectional data [4].

I find that a one standard deviation increase in air pollution leads to an increase in crime by 15 to 21 percent. The increase in violent crime in particular is robust to several robustness checks and placebo tests such as using an alternative definition of rice growing districts, extending the air pollution season and using a falsification test. The magnitude of the results suggests that the effect of air pollution on crime in a developing country might be larger than the estimates in the literature for the metropolitan cities in the developed world. Last, I also use some back of the envelope analysis to calculate the cost of the increase in crime attributable to air pollution exposure. I focus on psychological literature that can help explain the link between labor market outcomes and violence, such as frustration-aggression hypothesis (Berkowitz 1989) and general strain theory (Giulietti and McConnell 2020).

[3]The policy measures typically include a Pigouvian tax system, a pollution permit system, a cap and trade regime, a performance standard or adoption of environmentally-friendly technology.

[4]These include geo-spatial data on air pollution, fires, wind, temperature and precipitation, and socioeconomic data on labor market information, crime activity, health expenditure and attitude towards violence.

Effective crime reduction can help save millions by avoiding losses caused by costs of property damage, potential health costs for the victims resulting from violent crime, low socioeconomic activity level due to perceived threat to life and property, and costs associated with crime prevention efforts such as prosecution of offenders and increase in patrolling. As far as crime is concerned, even small effect sizes can translate into large amount of costs associated with the increase in crime (Herrnstadt et al. 2020) [5]. For developing countries, these higher effect sizes can translate into significantly higher costs relative to their gross output and institutional capacity to curb crime. The problem is aggravated by the fact that developing countries are constrained by the financial resources required to deal with the increase in crime.

Violent crime has been shown to increase almost linearly with respect to temperature (Ranson 2014). Similar patterns emerged in research on climate and aggressive behavior (Hsiang et al. 2013). Rainfall has also been documented as a driver of civil war and crime (Miguel et al. 2004; Doleac and Sanders 2015), through its impact on agricultural productivity (Blakeslee and Fishman 2018). Research also documents evidence of association between short run air pollution, and interpersonal conflicts and psychological outcomes such as ER visits for depression, suicide, suicide attempts and psychiatric admission rates (Lim et al. 2012; Szyszkowicz et al. 2010; Yang et al. 2011; Szyszkowicz 2007).

There is also a large body of literature in sociology, criminology and history on the relationship between crime and environmental conditions. Air pollution has also been found to have a link with physical aggression (Anderson and Bushman 2002). Research on the link between air pollution and aggressive behavior finds that exposure to pollution reduces cognitive performance and tolerance for frustration (Rotton 1983; Rotton et al. 1978). Another strand of this literature research explores the idea that air pollution may directly affect brain chemistry by causing fluctuations in the serotonin levels in the bloodstream (Gonzalez-Guevara et al. 2014; Murphy et al. 2011). Low levels of serotonin are known to be associated with increased aggression in humans and animals (Coccaro et al. 2011). Other research looks at how air pollution leads to oxidative stress and the inflammation

[5] For instance, Herrnstadt et al. (2020) estimate that a 2.1% increase in crime increases the cost of crime by at least \$1.8 million in United States.

of nerve tissues in the body and brain (Levesque et al. 2011; Van Berlo et al. 2010). This type of neuro-inflammation is also known to be linked to aggressive behavior in animals (Rammal et al. 2010).

Most economic literature focuses on labor market outcomes as a potential driver of crime (Giulietti and McConnell 2020; Becker 1968; Ehrlich 1973). Meanwhile, the aforementioned psychological literature on air pollution suggests that changes in brain chemistry can affect violence. While I discuss both in my discussion on mechanisms, I focus more on the former because of lack of availability of data on psychological factors. However, I still rely on two important theories from psychological literature that can help explain how labor market shocks can lead to changes in violent crime, namely Frustration-Aggression hypothesis and General Strain Theory (Berkowitz 1989); Giulietti and McConnell 2020) [6]. These theories help pinpoint the underlying psychological changes -as a result of a negative labor market shock- that can lead to an increase in violence.

My findings are consistent with the literature on the link between crime and air quality in the developed world which focuses on major cities such as London (Bondy et al. 2019), Chicago (Herrnstadt et al. 2020), and on counties in the United States (Burkhardt et al. 2019, Lu et al. 2018). This line of work identifies a statistically significant and positive effect of worsening air quality on crime, even at air quality levels fairly below current regulatory standards. Relying on Becker's (1968) rational choice theory of crime, Bondy et al. (2019) consider cognitive effects of air pollution as a potential mechanism; they focus on altered risk perceptions and risk preferences, and altered perceived payoffs from the crime as the channels linking air pollution and crime [7]. Bondy et al. (2019) do not find any evidence of altered risk perceptions on more air pollution days but do find that air pollution may alter perceived payoffs by raising the discount rate placed on future punishments. In terms of the the psychological mechanisms, their work is complementary to the literature on poverty's impact on cognition (Schilbach et al. 2016; Mani et al. 2013).

This paper makes several important contributions to the growing literature on the economic

[6] I discuss these theories and their relevance in detail in the section on Mechanisms

[7] Altered risk perceptions could lead to more risk taking which should be expected to also lead to increased tendency to commit crime. Altered perceived payoffs can be driven by an increase in the perceived benefit or a decrease in the perceived cost of the crime.

costs of air pollution. The existing literature on the link between air pollution and crime is still nascent. By providing evidence from developing countries, this paper strengthens the claim on the causal relationship between air pollution and criminal activity. Hence, this research adds to the growing evidence that curbing air pollution can reduce crime.

To the best of my knowledge, there is no existing literature that looks at the consequences of air pollution on crime in developing countries. As discussed above, the nature of air pollution in developing countries is different because their contribution to carbon emissions is low but their ambient air pollution is very high. Besides, they are also characterized by the lack of legislative framework and weak law enforcement. The analysis on the link between crime and air pollution in the world's metropolitan cities does not necessarily translate accurately to developing countries. Hence, it is important to develop an understanding of the link between air pollution and crime in this context.

Furthermore, this paper also adds to the research on the externalities from the agricultural sector for the general population. This research work adds to the literature on spillovers associated with the agricultural sector. It highlights the complex challenges faced by developing countries where agriculture is an important sector of the economy. This is particularly true for developing countries like Pakistan where rice is one of the most important foreign exchange earners [8]. Hence, it is crucial for these countries to develop environmentally sustainable crop practices that maximize agricultural production while minimizing it's externalities for the society. This research stresses the need for countries like Pakistan to adopt sustainable agricultural practices. Moreover, this paper considers crime as an externality and, hence, it emphasizes that the social costs of externalities from the agricultural sector are likely to be much higher than previously considered.

To the best of my knowledge, there is no existing research that investigates the link between air pollution and crime in a broader geographical context. I extend this analysis by including all the districts in the Punjab province of Pakistan. These include urban regions such as metropolitan and industrial cities but also rural regions where agriculture is the main economic activity. Hence, I

[8]Rice is among the top 5 major exports of Pakistan. Rice is also a major crop and foreign exchange earner in neighboring India.

establish a stronger association between air pollution and crime which is not just specific to the big cities.

Last, the literature linking crime and air pollution is still vague about the mechanisms that drive this correlation. I provide empirical evidence on at least one potential mechanism: there are seasonal shocks to earnings of older male workers because of air pollution [9]. In Punjab province, these older male workers are very likely to be the sole breadwinners of their family. The loss of income for this subgroup of the labor force might be crucial in explaining the link between air pollution and crime.

The remainder of the paper is arranged as follows. I provide a detailed explanation of the recent increase in air pollution in the Background section. This is followed by a section on the description of the Data used in this paper. The next section develops a theoretical model for linking air pollution and crime. In the next section, I discuss my identification strategy. In section 6, I discuss the Results from my analysis. Next, I test the robustness of my results through sensitivity analyses and placebo tests, followed by the section on heterogeneity in the effects of air pollution on crime. In section 9, I discuss the potential mechanisms, focusing on the labor market as a possible mediator of the results. This is followed by a section on Policy Implications where I perform some back of the envelope calculations to estimate the monetary costs of air pollution. The last section concludes and discusses the importance of the findings in this paper.

1.2 Background

Pakistan's Punjab province has faced seasonal smog in winters in the recent years (notably from the winter of 2015-16). Some North-Western states in India are facing a similar issue as well. This exponential increase in seasonal smog levels is attributed to the rice stubble burning by rice farmers (FAO 2018). Although Pakistan's carbon emissions are very low compared to the rest of the world, it is one of the most polluted countries in terms of ambient pollution. Pakistan faces this dilemma because of its vulnerability to climate change, and it's lack of implementation of preventive and

[9]The negative effect on earnings do not seem to be driven by seasonal trends in labor market activity.

adaptive measures for tackling climate change.

According to the data from the independent research organization IQAir (2020), Pakistan's annual average of smog concentration levels was seven times higher than the World Health Organization's (WHO) recommended threshold for "healthy air". The situation is particularly severe in the Punjab province of Pakistan where the average $PM_{2.5}$ concentration for 2019 was $108.5\mu g^3$ which is classified as "unhealthy for sensitive groups" by WHO (AQLI 2019). In some districts, the $PM_{2.5}$ reading crossed 350 for some days which is classified as "hazardous for all groups" in the population by WHO [10]. WHO recommends a health warning of emergency conditions at "hazardous" $PM_{2.5}$ levels.

A report produced by Food and Agricultural Organization in collaboration with the government of Punjab province in Pakistan (FAO 2018) points towards the practice of rice residue burning as a major contributors to the seasonal smog phenomenon. Specifically, more farmers now indulge into the practice of burning rice stubble after harvesting their crop which eventually produces smog. The wind direction then carries the smog across to other districts. The smog has been notably known to inhibit daily activities in major urban centers of the Punjab province.

The major rice growing season in Pakistan is from May to October. Rice is planted in May and June, and harvested in September and October, Following the harvest, farmers typically burn the rice stubble in the months of October, November and December (FAO 2018). A recent focus group interview by FAO in eleven major rice growing districts of Punjab found that rice farmers have increased rice stubble burning in the recent years (FAO 2018). FAO's (2018) report found that this increase is significantly higher in the months of October and November. In 2018, farmers burnt as much as 60% of the residue left in the rice fields.

The farmers' focus group survey mentioned above elicited various reasons for increase in the crop residue burning practice (FAO 2018). Farmers attributed the growing practice of rice residue burning to the decreased use of rice residue as animal fodder. This was widely practised in the

[10] WHO defines "unhealthy" $PM_{2.5}$ air quality as air pollution level that affects the health of some sensitive members of the population and "hazardous" air quality as air pollution that can seriously affect health of any member of the population.

past but it is not common anymore. Second, at least 44% farmers had increased the cultivation of non-basmati rice in the last two years. Non-basmati varieties are known to produce significantly higher residue which leads to rice residue being burnt in higher quantities. Farmers probably increased the cultivation of non-basmati rice varieties because of their higher yields [11].

Third, the use of combined harvester for harvesting rice is known to leave large amounts of rice residue. FAO's (2018) survey results show that as many as 84% of the farmers agree that the use of combined harvester has increased in the past five years. Furthermore, farmers deal with the increased rice residue by burning it, particularly in the month of November. The main reason for burning rice residue include saving on labor costs and time preparation required for preparing the field to sow the next crop [12].

Corresponding with an increase in rice stubble burning in 2015, there is a substantial increase in air pollution, or equivalently, a simultaneous decrease in average air quality in the months of October to February since 2015-16 (FAO 2018). Aerosol Optical Depth (AOD) is a measure of air pollution which increases as air pollution increases [13]. Figure 1 shows that, in the recent years, AOD in the months of November to February is significantly higher than in the months of March to October. This suggests that the air quality has recently worsened in the winter season, relative to rest of the year.

This timeline also corresponds to the various newspaper articles published in newspapers around this time, that emphasized the worsening smog phenomenon in the Punjab province (Khan 2015; Jalil 2016, Raza and Abubakar 2016; Jalil 2016). The first newspaper article I could find published on smog in Punjab was published in January 2015 titled "Lahore smog: It's not a natural phenomenon" [14]. There is another jump in the number of articles published on smog in Punjab around November 2016.

The report produced by Food and Agricultural (2018) in collaboration with the Punjab Depart-

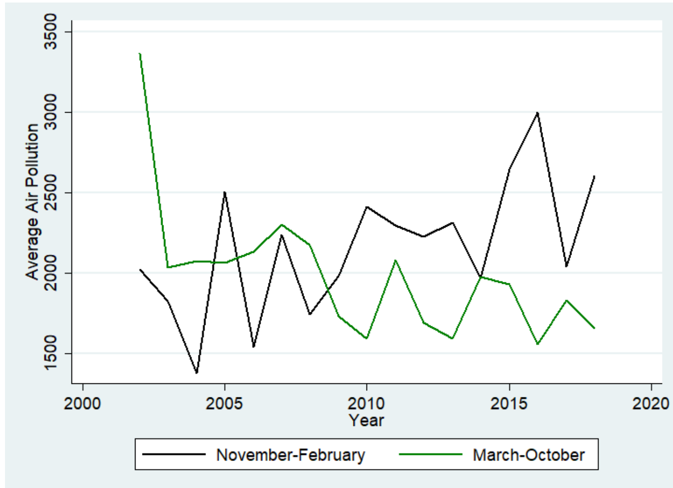
[11] Basmati varieties yield about 1,360 kg per acre while non-basmati varieties yield about 1,800 kg per acre.

[12] Most farmers in Punjab use their land in both cropping seasons. While rice is the major cash crop sown in the *Kharif* season, cotton and wheat are the major cash crops sown in the *Rabi* season which begins in January-February.

[13] The validity and accuracy of AOD is discussed in detail in the Data section

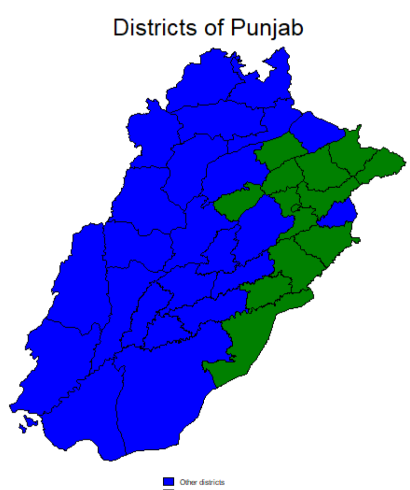
[14] Lahore is the capital of Punjab province.

Figure 1.1 Avg Air Pollution in November-February and March-September. Source: MODIS



ment of Agriculture (2018) provides a detailed discussion of how the smoke from burnt rice residue leads to an increase in air pollution in the form of smog. It demonstrates that the wind direction in the post-monsoon season of October-November carries the smoke to neighboring districts located towards the North and North-West of the rice growing districts. Figure 2 shows that the 12 major rice growing districts in Punjab province are located such that most of the remaining districts are located to their North and North-West. Thus, the remaining districts also get exposed to the burnt smoke coming in from the rice growing districts.

Figure 1.2 Rice Growing Districts, and Neighboring Districts to North & North-West. Source: Punjab Development Statistics



The wind and air pressure dynamics in the winter months of December, January and February help explain the prevalence of high levels of air pollution across the Punjab province. The wind direction and speeds are measured in terms of millibars (mbars) or hPa -both units are identical. During winter (or starting from December), a high localized pressure builds up at around 800hPa-850hPa which traps the particles in the air, including smoke, leading to the formation and prevalence of smog in the air. High air pressure prevails over most of Punjab in the winter months of December, January and February which traps the aerosols in the air leading to the prevalence of smog up until February.

Figure A1 in the appendix shows the wind direction and wind speed in the post-monsoon month of October, and in the winter month of January, respectively, over all of Pakistan. Figure A2 in the appendix provides a map with the provinces of Pakistan to better understand the exact position of the Punjab province. These measurements are taken at various altitudes, where altitude is measured in mbars. Since the smoke and other particles are trapped at an altitude of 800-850 mbars, the wind direction and speed at 800 mbar and 850 mbar are the most relevant for the purposes of this paper.

Figure A1 (a) in the appendix shows that the wind blows in from a direction of about 60-65 degree East in the month of October, all across Pakistan. When describing wind direction, an Easterly wind blows from the East towards the West. Hence, these South-Easterly winds blow towards the West and North-West [15] in October, carrying smoke particles burned in the rice fields all across Punjab. The wind direction becomes more Easterly in the winter month of January at about 80 degrees East, as shown in Figure A2 in the appendix. Hence, the smoke is not carried towards the North-West in January but, as discussed above, the rice stubble burning is mostly done by December.

As shown in Figure 2, the rice growing districts are located in the Eastern side of the Punjab province. Since the winds are blowing to the West and North-West, the smoke from the burnt rice residues gets carried to all across the province. The air pressure dynamics in the winter season trap smoke and other particles in the air, leading to increased air pollution (in the form of smog).

In other words, the stubble burning in the rice fields during the months of October, November

[15] Wind directions are usually reported in terms of where they are blowing from. For instance, a Southerly wind blows from the South to the North.

and December contributes an increase in the air pollution from November through February. Hence, the rice growing districts and their neighboring districts to the North and North-West bear the brunt of the increased smog levels from November to February in each winter season (FAO 2018). Seasonal rainfall can help alleviate the intensity of the smog temporarily (FAO 2018).

Two things can be concluded from this discussion. First, the smog phenomenon is seasonal. The recent intensification of smog in the Punjab province happened during the months of November, December, January and February is caused by smoke from the stubble burning in the rice fields in the months of October to December. The remaining months do not experience the recent intensification of smog or air pollution in Punjab. Second, the rice growing districts and their neighboring districts to the North and North-West are much more likely to experience smog than other districts [16]. The classification of rice growing districts is further discussed in the Data section.

It remains to be shown that the number of fires have indeed increased in the months of October, November and December when the rice residue may be burnt. In Figure 3 (a) I plot the total number of fires during the rice residue burning season of October, November and December. As shown in Figure 3, there is a substantial increase in the number of active fires recorded in the months of October to December, since 2016. Rice is harvested in September and October, and farmers are most likely to burn the residue in the month of November (FAO 2018). This is consistent with the farmers' claims about the intensification of this practice [17].

If the fires burned in the rice stubble burning season are indeed coming from the rice fields, the recent increase should not hold for the rest of the year. To verify this, I also plot the number of fires in the remaining months of a year in Figure 3 (b). There is no increase in the number of fires beginning from 2016. In fact, the total number of fires in these 8 months seem are slightly decreasing in the recent years. [18]. This descriptive evidence strengthens the claim that the recent increase in the number of fires -accompanied by the seasonal increase in air pollution- comes from

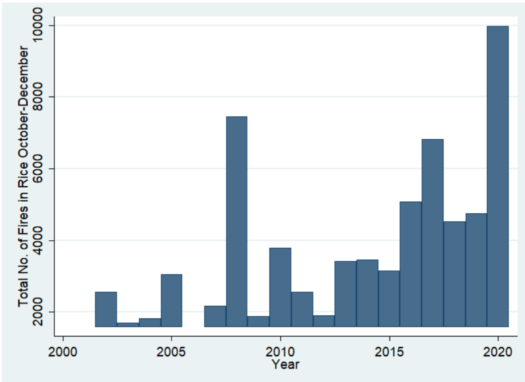
[16]Figure 2 shows the 12 rice growing districts of Punjab in green and all other districts in blue. As one can see, most districts in Punjab province are located to the North or North-West or West of the rice growing districts.

[17]2008 seems to have an abnormally high number of fires and is an anomaly in the trend, while the data for the year 2009 is partially not available.

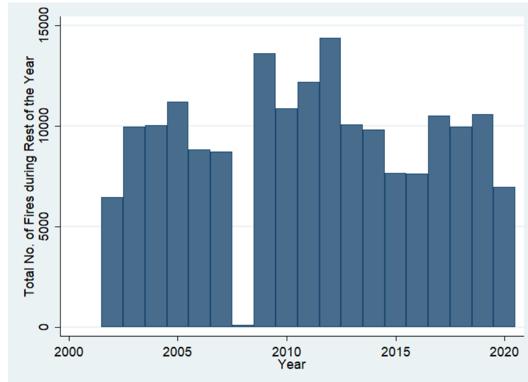
[18]Data for these months is not available for 2009.

Figure 1.3 Source: FIRMS

(a) Total Annual Fires from October-December



(b) Total Annual Fires in Rest of the Year



stubble burning practiced by rice farmers. Hence, it can be claimed that the dense smog experienced in the winter months in Punjab is associated with rice stubble burning in the rice fields. I will also strengthen this claim with empirical support later [19].

1.3 Data

The data comes from various sources. The main outcomes of interest are violent crimes and non-violent crimes. For this purpose, I use annual district level data on different types of crimes -such as murder, rape, assault, theft etc.- for Punjab province of Pakistan. These statistics are available in annual reports produced by the Punjab government known as Punjab Development Statistics, and they are available from 2002 to 2018.

Crimes are classified into 14 different types in the data. These include attempted murder, burglary, cattle theft, assault on government servants, dacoity (an act of violent robbery), hurt, kidnapping, motor vehicles theft, murder, rape, rioting, robbery, ordinary theft and miscellaneous crimes. Commonplace crimes such as ordinary theft and robbery are significantly higher in number than other crimes such as assault and murder.

The second set of information is about annual rice production and area sown with rice in each district. I use data on annual district level rice production in thousands of tonnes and rice area in

[19] I show in the Robustness Analysis section that the increase in the number of fires increases the average air pollution not only in the months of November, December, January and February but also throughout the year.

thousands of hectares from Punjab Development Statistics. This information is available for the years 2003 to 2017. The definition of rice growing districts also entails some discussion. I define rice growing districts as those whose production is greater than the 75^{th} percentile of Punjab's total rice production for at least 10 years. 12 out of 36 districts of Punjab get classified as the rice-growing districts according to this strategy.

To ensure that the correct rice growing districts are chosen, I compare my classification of 12 rice growing districts with the 11 rice growing districts FAO (2018) used in their farmers' survey. 9 rice growing districts are the same in my classification and in FAO's survey. The remaining two districts in FAO's survey are the two largest districts in the Punjab province -namely Lahore and Faisalabad- and are probably only included because of their significantly larger population and market size.

My classification of 12 rice growing districts is also fairly robust. The 12 districts classified as rice growing districts do not change if I use area sown with rice instead of rice production as the classification variable. The classification of these 12 districts also does not change if I create the percentiles without grouping the data by year. Since the longitudinal data on rice production is available for a long time period -16 years in total -the classification also signals that the major rice growing districts in Punjab have stayed the same in the past [20].

My main explanatory variable is air pollution. The air quality data comes from NASA's Land Processes Distributed Active Archive Center (LP DAAC). The specific data product used is MODIS Terra and Aqua MAIAC Land Aerosol Optical Depth (AOD). I used Google Earth Engine to write a Java Script for downloading the AOD data from 2002 to 2019. The AOD is collected two to four times every day, on average, at a grid resolution of 1km. It is usually retrieved at altitudes less than 4.2km, except when smoke or dust aerosol is detected. AOD measures "the amount of light lost due to the presence of aerosol on a vertical path through the atmosphere" (NASA 2019).

AOD is a key component of smog. These aerosols are produced by urban and industrial

[20] In one of my robustness checks, I also change the classification of rice growing districts to the 11 districts where FAO (2018) conducted surveys with the rice farmers. As I will show later, this change does not affect the qualitative interpretation of the results in any way.

sources, fires, volcano eruptions and dust storms (NASA 2019). AOD has been used previously in the literature for estimating the impact of air pollution on outcomes of interest such as infant mortality (Foster et al. 2009). For the purposes of this paper, AOD is a relevant measure of air pollution because it measures the suspended particles in the air including smoke. Since I am leveraging the variation in smoke from stubble burning as a source of air pollution, AOD serves the purpose well.

The data provides the sum of AOD observed for a given number of pixels at a given time of the day. There can be up to 4 observations per day. The number of pixels for each observation are different so the raw data is not standardized. Since pixel size is different for each observation, a single observation of AOD cannot be compared with another in terms of magnitude, without some sort of standardization. Therefore, I take a weighted average of these values of average AOD per pixel to calculate “average AOD per pixel" for each observation [21]. I use this value to obtain monthly, seasonal and annual averages for “average AOD per pixel".

Next, I use the fire data to understand the relationship between air pollution and fires burnt in the rice growing districts. The fire data comes from NASA’s Fire Information for Resource Management System (FIRMS). It records and then processes the active fire locations using MODIS Fire and Thermal Anomalies Product. The active fire locations are recorded once every day. These fires are recorded on a grid resolution of 1km.

Under perfect observing conditions (i.e. with homogeneous land surface and with clear atmosphere), fires covering the area as small as $50m^2$ can be detected. In other words the lower bound on the size of fires that can be detected, is fairly large area and it suggests that something as small as a campfire will not be included as an active fire. Therefore, the number of active fires is not likely to suffer from measurement error because of very small fires which cannot be counted as fire events.

Following the similar procedure described above for AOD, I used Google Earth Engine to write a Java Script for downloading the fire data from 2002 to 2020. I generate weighted averages of

[21] This involves multiplying each observed AOD value by its pixel size, and dividing it by the sum of all pixel values observed.

average number of fires per pixel (NASA 2018) and use them to generate monthly, seasonal and annual averages of “average active number of fires per pixel".

The wind direction, wind speed, rainfall and temperature data come from the re-analysis climate data produced by European Center for Medium Range Weather Forecasts (ECMWF). The monthly averages of wind direction and wind speed data are retrieved at a pressure of 850hPa which translates to an attitude of about 1.46 kilometres. I chose to retrieve this data at the 850hPa pressure level because the FAO report (2018) -discussed in the Background section- suggests that the formation of smog in the winter months in the Punjab province takes place at an air pressure of 800hPa to 850hPa. ECMWF also provides monthly averages of rainfall and temperature data. I use this data to generate seasonal and annual averages for the wind direction, wind speed, rainfall and temperature variables respectively. All these variables have data available for the years 2002 to 2020.

I also use information on various socioeconomic statistics in this paper. District area and population are used to normalize the district crime levels. This information is publicly available through Pakistan Bureau of Statistics. The data on district population and the district area comes from the National Census of 2017.

I also use individual and district level data on education, health and employment information. This data is used for exploring the mechanisms as well as for adding controls to different regression specifications. The information on individual employment status, monthly income, number of days worked per month, health issues and years of education comes from Pakistan Living Standards Measurement Survey (PSLMS) and Household Income and Expenditure Survey (HIES). Both PSLMS and HIES contain information on education, health and employment. The PSLMS data is available for the years 2004-05, 2006-07, 2008-09, 2010-11, 2012-13, 2014-15 and 2019-20. The HIES data is available for the years 2005-06, 2007-08, 2011-12, 2013-14, 2015-16 and 2018-19. Additionally, I use the information in the Multiple Indicator Cluster Survey (MICS) for the year 2017-18, on men’s attitude towards violence on their spouses. Unfortunately, this information is not available in the previous rounds of MICS for Punjab.

A table of summary statistics is provided in the appendix A. Table A1 in the appendix provides the number of observations, mean and standard deviation of different variables. The average number of violent crimes is about 550 which is much lower than the average number of non-violent crimes which is 6,337. However, this average is driven by the very high number of crimes classified as “miscellaneous". If the miscellaneous crimes are excluded, the average of non-violent crimes falls to about 804. Table A1 in the appendix also shows that the average level of AOD and the average number of fires are higher for the winter season than annual average and the average for the summer season.

The mean wind direction in Table A1 in the appendix is about negative 0.684 in radians. This is the mean wind direction during the months of October, November and December when the crop residue is being burnt in the rice growing districts. This equals about negative 40 in degrees. A negative wind direction signifies wind coming in from the East. The mean wind direction in the report produced by FAO (2018) for the month of October is about 60 degrees East. My wind direction is slightly different because it takes into account the wind direction from the rice growing districts only while the FAO's calculation is for the whole of Pakistan and North India. For the purposes of identification, this does not affect the results because the overall direction of the wind remains same in the sense that it is blowing from from the South-East towards the North-West.

1.4 Conceptual Model

I follow the approach of Giulietti and McConnell (2020) a la Becker (1968) and Ehrlich (1973) in developing a theoretical model that links air pollution to crime. Under this framework, a rational individual commits crime if the net benefit from crime exceeds the benefit from not committing a crime or from engaging in the legal labor market.

Let D_i be an indicator function that takes the value 1 if an individual commits a crime. The net benefit of committing a crime is the benefit of the crime minus the cost of the crime. Let $B(Z_i)$ be the benefit from committing an offense where Z_i includes monetary pay off and all other non-pecuniary benefits from crime. Let $\chi_i/P_i^{\alpha_c}$ be the perceived cost of committing a crime where χ_i includes strength of the police force, probability of conviction and punishment fine. Similarly,

$P_i^{\alpha_c}$ is the change in perceived cost of crime due to air pollution P, and α_c depends on the type of crime c where $C \in \{v, nv\}$ where v represents violent crime and nv represents non-violent crime [22]. Assume $P_i \geq 1$ where $P_i = 1$ implies air pollution has no effect on an individual's cost of crime.

Further, let $W_i(P_i)$ be the outside option [23] determined by air pollution levels. The expected utility from committing a crime can be defined as:

$$U_i \ = D_i[B(Z_i) - \frac{\chi_i}{P^{\alpha_c}}] + (1 - D_i)W_i(P_i).$$

In the above framework, an individual commits a crime if and only if $[B(Z_i) - \frac{\chi_i}{P_i^{\alpha_c}}] \ \geq W(P_i)$. Or equivalently:

$$\chi_i \ \leq \ [[B(Z_i) - W(P_i)]P_i^{\alpha_c}].$$

The above expression provides a distribution for the crime rate C based on a distribution in the population where $C \ = \ F_x \ [[B(Z_i) - W(P_i)]P_i^{\alpha_c}]$ [24]. One parameter of interest here is α_c which depends on whether a crime is a violent crime or non-violent crime. Here, α_c can be interpreted as the cognitive ability required to commit a crime. I assume $\alpha_v > 1$ and $0 < \alpha_{nv} < 1$ [25]. Hence, $P_i^{\alpha_v}$ increases the crime rate faster than $P_i^{\alpha_{nv}}$ The other parameter of interest is $W(P_i)$ or the outside option which decreases with an increase in air pollution P_i, thus, once again increasing the overall crime rate.

1.5 Empirical Strategy

The identification strategy exploits the timing of the residue burnt in the rice fields and the timing of the increase in air pollution. This information can be squeezed into a flow chart. It is important

[22] The rationale for treating violent and non-violent crimes as mutually exclusive is in line with the discussion in the Introduction section on the psychological effects of air pollution, which explains how air pollution can increase the tendency to be violent and aggressive, through changes in brain chemistry and inflammation of certain tissues. I will elaborate further on this point when I discuss the Results later.

[23] The outside option can be the labor market wage. Air pollution can affect the wage rate through its affect on cognitive performance, labor productivity and labor market participation.

[24] Note that this is focusing on the increase in crime due to air pollution, and not the increase in crime due to air pollution.

[25] Air pollution increases frustration levels and aggression but reduces cognitive ability. Hence α_c can differ for violent and non-violent crimes. In other words, psychological factors have stronger implications for violent crime compared to non-violent crime.

to underscore the timeline since it is key for identification. Figure A3 in the appendix presents this in the form of a flow chart. Rice is planted in May and June, and harvested in September and October. Following the harvest, rice residue in the rice fields is most likely to be burnt in the months of October, November and December which leads to an increase in air pollution in the months of November, December, January and February. As mentioned in the Introduction section, the increase in air pollution to extremely dangerous levels is expected to cause labor market distortions and psychological factors such as increased frustration and aggression. Hence, the labor market shocks and the psychological factors are expected to channel an increase in crime and violent attitudes.

Since the rice stubble burning phenomenon is seasonal, the ideal identification strategy would use monthly or seasonal data to tease out the seasonal effect of air pollution on crime for the months of interest. However, the crime data available is annual in nature; monthly or seasonal crime data is unfortunately not publicly available. Hence, I devise an alternative identification strategy which is discussed below.

I use an instrumental variable approach to define my identification strategy. Wind direction, as I will argue later, is a suitable instrument that satisfies the relevance and exogeneity conditions. I exploit the fact that, in the months of October through December, districts located upwind will receive relatively more smoke from rice growing districts than districts located downwind. This will lead to an increase in air pollution in the winter months of November, December, January and February. For these four months, the increase in air pollution will tend to be relatively higher in the upwind districts than in the downwind districts.

The main explanatory variable, therefore, is the average air pollution -measured by AOD- in the four winter months of November, December, January and February [26]. I define this variable as AOD_w_{jt} which measures the average air pollution in the aforementioned four winter months in

[26] A caveat here is that the winter months of November, December, January and February considered here are from the same calendar year. Technically, the months of January and February from the next calendar year should be considered. However, in that case, it becomes impossible to relate the air pollution data with the crime data since the crime data is annual in nature. To account for this timing issue, I take the average of the instrument for the current year and the previous year. The instrument used throughout in this paper is technically the average of the instrumental variable for the current year and the previous year.

district j in year t.

A potential issue here is that it is difficult to assign a meaning to the AOD values. Unlike $PM_{2.5}$ or PM_{10}, there are no defined thresholds of AOD which would define a certain AOD value as either safe, unhealthy or dangerous. Hence, I use normalized values (otherwise known as z-scores) in all my empirical specifications, for the main variable of interest AOD_w_{jt}.

For the estimation linking air pollution to crime,the main equation is:

$$log(Y_{jt}) \ = \ \beta_1 AOD\_w_{jt} \ + \ X_{jt}B \ + \ \phi_t + \gamma_j + \omega_k * t + \epsilon_{jt} \tag{1.1}$$

where Y_{jt} is the total number of crimes in district j in year t normalized by the district area per 1,000 square kilometres. AOD_w_{jt} is the normalized value of Aerosol Optical Depth (AOD) in the four winter months. X is a vector of controls which includes rainfall, temperature, number of fires, rice production, rice area and district level socioeconomic controls such as mean years of education for a district. ϕ_t are year fixed effects, γ_j are district fixed effects, $\omega_k * t$ is division specific time trend [27] and ϵ_{jt} is the random error term.

The amount of rice residue burnt in one season depends on the rice production and area sown with rice in a district. As discussed in the Introduction, rice is a major crop in Punjab and also one of the top 5 foreign exchange earners for Pakistan. This suggests that rice production is a major economic activity in some districts. Since economic conditions can determine both rice production and crime in a district, the results from the OLS regression will be biased.

The bias can be upwards or downwards. For instance, growth in economic activity can present more opportunities to commit crime. However, economic growth will improve society's welfare which can decrease an individual's likelihood to commit crime. Thus, not only are the results from an OLS regression likely to be biased but the sign of the bias is also unclear. To obtain estimates which are not confounded by this unobserved bias, I follow an instrumental variables approach.

[27] Division is an administrative level above the district and below the province. In the Punjab province there are 7 divisions and 36 districts.

The instrument is constructed as follows. I take the average annual wind direction, Dir_t^T, from the 12 rice growing districts in the months of October, November and December. This is the wind direction in the months in which rice residue is burnt.

Next, I account for how upstream or downstream a district is with regards to the wind direction from the rice growing districts. For this purpose, I first calculate the average latitude of the rice growing districts. I then calculate the azimuth from the rice growing districts to each district [28]. I subtract Dir_t^T from the azimuth of the district lat_j. Subsequently, the absolute value of $lat_j - Dir_t^T$ gives the position of district j with respect to the wind direction. It would equal zero if the district is exactly in the same direction as the wind direction. In other words, it will equal zero for any district exactly upwind. Any deviation from zero would mean that the district moves further downwind which would reduce the impact of wind direction on the air pollution. $lat_j - Dir_t^T$ accounts for the direction from which the wind is brought in. If a district is located in the same direction from the rice growing districts as the direction of the wind, it will receive more air pollution from rice stubble burning. Hence, there is a negative relationship between the instrument and the average air pollution in a district.

However, the above instrument assumes that any polluted air brought in from the rice growing districts will affect all other districts equally, regardless of their distance from the rice growing districts. Therefore, I weight the instrument by the mean distance from the rice growing districts [29] to get the instrument $Wind\_Distance_{jt}$.

The instrument is plausibly exogenous. Wind direction has been used as an instrument extensively in papers linking air pollution to an outcome of interest. The most relevant paper in this regard is Herrnstadt et al. (2020) who use wind direction in Chicago as an instrument for air pollution. Another relevant paper is by Angel and Vogl (2019) who use wind direction from fires burning in sugarcane fields to link these fires with child health outcomes.

In any case, an activity like crime is highly unlikely to be driven by the wind direction itself.

[28]The azimuth is the angle between a point of origin and point of destination. For example, Chicago, Illinois is at Latitude 41.8781 and New York City is at 40.7144. However, the azimuth between the two cities is 91.95 degrees.

[29]For the non-rice growing districts, the distance equals the mean distance from all 12 rice growing districts; and for each rice growing districts, distance equals the mean distance from 11 other rice growing districts.

Wind direction is usually not driven by most economic outcomes of interest and it is definitely not likely that it will be driven by criminal activity in a district.

The second condition an instrument must satisfy is the relevance assumption. The standard threshold for a strong instrument is the first stage F-stat value of at least 10. For this purpose, the first stage estimation equation needs to be estimated. The corresponding first stage equation to equation 1 can be written as:

$$AOD\_w_{jt} \;=\; \delta_1 Wind\_Distance_{jt} \;+\; X_{jt}\Delta \;+\; \lambda_t + \pi_j \;+\; \theta_k * t \;+ \mu_{jt} \tag{1.2}$$

where $Wind\_Distance_{jt}$ is the instrument discussed above. X is a vector of controls similar to the one included in equation 1, λ_t are time fixed effects, π_j are district fixed effects and $\theta_k * t$ is the division-specific time trend.

I present the results from the first stage regression of equation 2 in Table 1. Columns 4 to 6 run the same regression equation as Columns 1 to 3 but they come from the instrumental variable regression of the single lagged variable of crime on air pollution [30]. The coefficient on the instrument is negative as expected, and it is statistically different from zero in all the 6 regression specifications presented here. The first stage Kleibergen-Paap F-stat is above 10 in all the specifications provided here [31]. The lowest value of the statistic is 16.69 in column 3 and the highest value is 29.22 in column 4. Hence, the instrument is strongly relevant with a first stage F-stat well above 10.

Additionally, it might be the case that the area sown with rice in major rice growing districts determines the amount of air pollution suffered by different districts. I account for this in Table A4 in the appendix by weighting the instrument by the mean area sown with the rice crop in the 12 rice growing districts in the base year -that is, 2002. There is no notable change in the coefficient on the instrumental variable as well as the first stage F-stat.

[30] Most of the air pollution happens in November and December, with data suggesting that November is the most polluted month. Additionally, with crime data being annual in nature, I am forced to consider the months of January, February, November and December for the same year, instead of considering November and December of previous year, and January and February of the current year. Therefore, I examine the lagged effects of air pollution on crime, which also serve as a robustness check.

[31] More regression specifications were also run. They are provided in Tables A2 through A4 in the appendix. The first stage F-stat is above 10 in all the specifications

Table 1.1 First stage results.

Air Pollution in the Winter Months

	(1) First Stage	(2) First Stage	(3) First Stage	(4) First Stage	(5) First Stage	(6) First Stage
Wind_Distance	-0.0028***	-0.00266***	-0.00277***	-0.00298***	-0.00298***	-0.00277***
	(0.00054)	(0.00060)	(0.00068)	(0.00055)	(0.00055)	(0.00068)
F stat	27.47	19.49	16.69	29.22	29.22	16.69
Observations	611	611	428	575	575	428
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	Yes	Yes	No	Yes
Rice Controls	No	No	Yes	No	No	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
Avg. Instrument	1262	1262	1262	1262	1262	1262
Avg. Air Pollution	2126	2126	2126	2126	2126	2126

Robust standard errors in parentheses

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

Notes: The dependent variable is the average air pollution in months of November, December, January and February. The instrument is the wind direction -as explained in the paper- for the months October, November and December. Columns 4 through 6 are results from the IV regression of crime on lagged air pollution and hence, they lose one year of observations. Columns 3 and 6 include data on rice production, rice area and other district level controls. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level.

This robust first stage result establishes that, in the months of October, November and December, the wind coming in from the 12 rice growing districts does contribute substantially to the increased air pollution during the winter months of November, December, January and February [32].

[32] I support this evidence further in the Robustness section where I show that fires burnt in the rice growing districts do indeed increase the air pollution in the winter months as well as the annual air pollution.

1.6 Results

The psychological effects of air pollution include reduced cognitive ability, increased aggression and reduced tolerance for frustration. This suggests that air pollution may affect violent crimes differently than other crimes. This also helps explain why it is a common practice to separate violent crimes from other crimes (Herrnstadt et al. 2020; Bondy et al. 2019) in the literature on the relationship between air pollution and violence. Hence, it makes sense to disaggregate the crimes into violent and non-violent crimes.

Second, the unavailability of monthly crime data complicates the identification strategy. The fires are burnt in October, November and December. The increase in air pollution, however, tends to prevail until February of the next calendar year. Thus, there is a high likelihood of the lagged effects of increased air pollution through rice residue burning. Therefore, I also report the one year lagged effect of air pollution on crime.

Before I present the results obtained from the instrumental variables regression, I present results from the OLS regression of equation 1. The results are presented in Table A5 in the appendix. Column 1 only includes the district and time fixed effects and Column 2 adds division specific time trend. Columns 3 and 4 use the specification as in Columns 1 and 2, and present the results for the lagged effect of air pollution on violent crime. Column 5 also adds controls such as rice production, rice area and other district level controls. The dependent variable, log of annual violent crimes, is weighed by the district area per 1,000 square kilometres.

In order to account for the possibility that correlation across years in the same district can result in invalid and downward biased standard errors [33], I cluster the standard errors at district level. However, the number of districts is 36. With a low number of clusters, the standard asymptotic tests can over-reject the null hypotheses of no effect (Cameron et al. 2008). Therefore, I bootstrap the standard errors obtained through clustering at the district level, according to the wild cluster

[33] This correlation can exist in the main explanatory variable of interest because of the trends in the air pollution variable. The wind direction randomly assigns some districts to more air pollution than others. However, this unit of assignment is at district level and not at district by time period.

bootstrap method defined by Cameron et al. (2008) [34].

The coefficient is positive in all the 5 specifications reported in Table A5 in the appendix. It is only statistically different from zero in Columns 1 and 3. Column 1 shows that a one standard deviation increase in air pollution increases violent crimes by about 3.7 percent. Column 1 also reports the highest coefficient in Table A5 in the appendix. The smallest coefficient is in Column 5 at 0.89 percent which is statistically not different from zero.

Table A6 in the appendix reports the same 5 specifications for non-violent crimes. None of the coefficient is statistically different from zero. Besides, only the coefficient in Column 1 is positive, all other coefficients have a negative sign. While the OLS results are biased for reasons discussed in the previous section, the difference in the coefficients for violent and non-violent crimes does suggest that air pollution affects violent and non-violent crimes differently.

The direction of the bias entails some discussion. OLS estimation only accounts for general levels of air pollution. The local sources of air pollution can be a result of increased economic activity: an increase in incomes, for instance, may lead to an increase in car ownership which can contribute to local anthropogenic air pollution. Similarly, increased industrial activity can also contribute to local air pollution. The OLS estimation is unable to isolate the positive effects of these economic activities on societal welfare. An increase in incomes, for instance, may lead to a reduction in crime. Increased car ownership may also help reduce the number of crimes committed for passengers who commute after sunset. This suggests that the results from the OLS regression are biased downwards.

Next, in Table 2, I present the results from the instrumental variables estimation of equation 1. The dependent variable in Table 2 is log of annual violent crimes which is weighed by the district area per 1,000 square kilometres. Column 1 only includes district and year fixed effects while column 2 also adds division-specific time trend. Columns 3 and 4 present the same specifications as Columns 1 and 2, respectively, for the lagged effect of air pollution on crime. The results should be interpreted as the percent change in crime per 1,000 square kilometres due to a one standard

[34] In all the results presented in this paper, I present the usually reported standard errors from the regression in round parentheses and the bootstrap p-values in the square parentheses.

deviation increase in air pollution.

Table 1.2 The effect of air pollution on violent crimes.

Log of Annual Violent Crimes per 1000 Sq. Km	(1) IV	(2) IV	(3) IV Lagged Effects	(4) IV Lagged Effects
AOD_w_{jt} (Standardized)	0.21361**	0.15150	0.24904***	0.21202**
	(0.10685)	(0.09760)	(0.08112)	(0.08324)
Bootstrap P-value	[.03103]	[.20821]	[.00601]	[.01401]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Rice Controls	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No
Observations	611	611	575	574
R-squared	0.905	0.918	0.907	0.922
Avg. Air Pollution	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801
Avg. Crime	549.5	549.5	550.4	550.4

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual violent crime in a district weighted by district area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Column 1 shows a 21.4 percent increase in crime due to a one standard deviation increase in air pollution. The coefficient is statistically significant at 90% significance level. When the division-specific time trend is added in column 2, the coefficient drops to 15.2 percent and it is not statistically different from zero any more. However, Columns 3 and 4 show that the effect of air pollution on crime is larger with a lag of one year, with a coefficient of 24.9 percent and 21.2 percent respectively. The coefficients in both columns are statistically different from zero at 95% significance level.

From the results presented in Table 2, it seems that the effect of air pollution on violent crime is larger and more robust in the next year. This makes sense because the increase in air pollution starts as late as November and prevails until February of the next calendar year. In Table 3, I add more controls: Column 1 of Table 3 includes district level controls such as district literacy level -measured by mean years of education- and mean number of days worked per month. Column 2 also adds controls related to rice production such as area sown with rice and rice production. Columns 3 and 4 repeat the same specifications as Columns 1 and 2 but for the lagged effect of air pollution on crime. While adding these additional controls, some observations are lost because the data on rice production is only available from 2002 to 2017 while the data on district level controls is not available for 2017.

The coefficient on normalized variable of AOD is positive and statistically different from zero in all the 4 different specifications in Table 3. Columns 2 and 4 present results from the fully specified model as they include all the fixed effects, a division specific time trend and full range of controls. The highest coefficient is reported in Column 2 which shows that a one standard deviation increase in air pollution increased crime by about 21.8 percent. The one year lagged effect shows a 17.5 percent increase in crime due to a one standard deviation increase in previous year's pollution.

The coefficient sizes reported here are significantly larger than the coefficient sizes reported in the literature (Herrnstadt et al. 2020; Bondy et al. 2019). For instance, my estimates for all types of crimes are at least 5 times larger than the increase in violent crime reported by Herrnstadt et al. (2020). This is likely to be because of three reasons. First, the two papers cited here discuss air pollution in Chicago and London respectively, which have significantly lower levels of air pollution than the Punjab province in Pakistan does. As discussed in the introduction section, air pollution in some of the major urban centers in Punjab province remains at unhealthy to dangerous levels during most of the winter season. A significantly higher level of pollution, thus, leads to significantly higher social costs for the society in terms of crime.

Second, my identification strategy allows me to focus on the effect of increase in air pollution occurring specifically because of the rice stubble burning in rice growing districts. I am able to

Table 1.3 The effect of air pollution on violent crimes (with additional controls).

Log of Annual Violent Crimes per 1000 Sq. Km				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
			Lagged Effects	
AOD_w_{jt} (Standardized)	0.20029***	0.21780***	0.15787**	0.17498**
	(0.06532)	(0.07445)	(0.06254)	(0.07215)
Bootstrap P-value	[0.00000]	[.00300]	[.01902]	[.01401]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	Yes	Yes	Yes	Yes
Rice Controls	No	Yes	No	Yes
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Observations	490	428	454	428
R-squared	0.950	0.946	0.961	0.957
Avg. Air Pollution	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801
Avg. Crime	549.5	549.5	550.4	550.4

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual violent crime in a district weighted by district area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. Columns 1 and 3 include other district level controls and Columns 2 and 4 additionally control for rice production variables. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

disentangle this effect from all other sources economic activity that can contribute to anthropogenic air pollution such as traffic and industry . While the air pollution generated through these activities can increase local crime, they can also help reduce it by, for instance, increasing employment opportunities and by raising the opportunity cost of crime. This means that any benefits to the society of these socioeconomic activities do not bias the results downwards.

Third, classical measurement error can exist in the satellite measurements of air pollution. Classical measurement error in the explanatory variable can bias the estimates down towards zero.

However, an instrumental variables approach will correct for the classical measurement error as long as the instrument is uncorrelated with the local measurement error (Angrist and Krueger 2001). In our setting, this condition is at least partially satisfied because the instrument's components -that is wind direction and district azimuth- are not likely to be correlated with measurement error in air pollution levels.

To strengthen the claim that the results presented here are indeed causal, I also present results from the reduced form regression in Table A7 in the appendix. Arguing causality becomes harder if the reduced form estimates are statistically not different from zero and/or do not have any economic significance in terms of their size (Angrist and Pischke 2008). I run the following specification for the reduced form analysis:

$$log(Y_{jt}) = \eta_1 Wind\_Distance_{jt} + X_{jt}H + \iota_t + \kappa_j + \nu_k * t + \upsilon_{jt} \tag{1.3}$$

where $log(Y_{jt})$ is the total number of violent crimes in district j in year j normalized by the district area per 1,000 square kilometres. X is a vector of controls similar to the controls in equations 1 and 2, ι_t are time fixed effects, $kappa_j$ are district fixed effects and $\nu_k * t$ is division specific time trend; and η_1 is the main coefficient of interest.

Since the instrument is constructed such that both the components of the instrument cause a decrease in air pollution, the reduced form would measure the impact of a one standard deviation reduction in the instrument on crime. To avoid this confusion and to ease the interpretation, I multiply the instrument by -1. This will mean that the reduced form estimates will estimate the impact of a one standard deviation increase in the instrument. Specifically, it will estimate the impact of a district becoming more upwind or an increase in positioning of a district towards the wind direction from the rice growing districts.

Other than Column 2, all the estimated coefficients reported in Table A7 in the appendix are positive and statistically different from zero. The coefficient in column 1 means that a one unit increase in the instrument increases crime by about 0.060. Column 3 reports the highest coefficient at 0.074 percent. Column 5 is the fully specified model which reports the a 0.048 percent increase in air pollution due to a one unit increase in the instrument. Given the standard deviation of the instrument, a one standard deviation reduction in this difference translates to a 30 percent increase in crime. Hence, the wind blown in from the rice growing districts in the months of October to December does have a positive and statistically significant effect on annual crime.

It must also be pointed out that the crimes considered here are occurring in a diverse range of socioeconomic settings. The regions include metropolitan districts such as Lahore which is the second largest city in Pakistan and Faisalabad which is the industrial hub in Punjab. They also include districts like Attock and Jhelum towards the north which are medium sized towns located in the Potowar plateau with rain-fed crop production. Most of the central and south Punjab, on the other hand, consists of fertile lands where rice, wheat, cotton and sugarcane are grown on large scale; these are the regions which experienced an immense increase in agricultural productivity in the 1960s owing to the Green Revolution. In addition, a small part of Southern Punjab also consists of a desert.

Hence, the results presented here link crime and air pollution in a wide geographical and socioeconomic setting. Therefore, it will be wrong if policy makers just focus on the large metropolitan cities and urban districts when it comes to addressing this issue. It is just as important to consider, for instance, the areas where agricultural activity forms the backbone of the local economy. These regions can also suffer from an increase in crime due to air pollution, and one effective way of reducing crime, hence, could be to reduce air pollution.

These results also show that air pollution has an association with crime in developing countries. The literature on the social costs of air pollution in developing countries is mostly limited to consequences for health and, in particular, mortality (Heft-Neal et al. 2019; Foster et al. 2009). Meanwhile, the effect of air pollution on children's educational performance is also well known (Ebenstein et al. 2016). The concerns about the social costs of air quality in developing country need to be more holistic. It is highly likely that the social costs of air pollution in developing countries are much higher than previously considered.

A related caveat here is that developing countries have significantly less stringent environmental regulations. Any regulations in place are often not implemented because of limited capacity of law enforcement institutions. As far as criminal activity is concerned, developing countries lack a system for crime mitigation and prevention. Police departments might not have enough monitoring resources in terms of manpower and patrolling vehicles. Legal and judicial system might contain significant loopholes making it difficult to ensure deterrence and detection of offenders. These issues can aggravate the adverse impacts on economic growth for developing countries.

Last, these results establish that agricultural activities and, in particular biomass burning, have important consequences for the welfare of the society. In other words, agricultural biomass burning is a very important source of environmental pollution which has broader consequences than previously considered. Hence, in line with the findings of Rangel and Vogl (2019), I find that agricultural sector's contribution to environmental degradation has associated social costs. The results suggest that the social costs of harmful agricultural activities are much higher than those currently considered by policy makers. Current literature is almost completely focused on the local sources of urban ambient pollution. My results suggest that ambient pollution -in any setting be it urban or rural- is significantly affected by farmer practices that contribute to air pollution.

Next, I will discuss the effect of air pollution on non-violent crimes. The evidence on the effect of air pollution on non-violent crimes has been mixed at best (Herrnstadt et al. 2020; Bondy et al. 2019). In Tables 4 and 5, I present the results from the instrumental variable regression of equation 1 on non-violent crimes. The dependent variable is log of annual non-violent crimes in a district, weighted by the area per 1,000 square kilometres. Table 4 contains the same specifications as Table 2, with the only change being the outcome of interest. As with Table 2, Columns 3 and 4 present the same specifications as Columns 1 and 2, respectively, for the lagged effect of air pollution on crime.

In Column 1 of Table 4, a one standard deviation increase in air pollution increased non-violent crime by about 17.6 percent. The coefficient is statistically significant at 95% significance level. However, when the division specific time trend is added in Column 2, the coefficient size drops down to 9.8 percent and it is no longer statistically different from zero. In Columns 3 and 4 where

Table 1.4 The effect of air pollution on non-violent crimes.

Log of Annual Non-Violent Crimes per 1000 Sq. Km				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
			Lagged Effects	
AOD_w_{jt} (Standardized)	0.17758**	0.09756	0.08974	-0.02161
	(0.08496)	(0.09024)	(0.05591)	(0.06569)
Bootstrap P-value	[.04805]	[.29930]	[.12713]	[.78278]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Rice Controls	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No
Observations	611	611	575	574
R-squared	0.964	0.972	0.972	0.977
Avg. Air Pollution	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801
Avg. Crime	6337	6337	6423	6423

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual non-violent crime in a district weighted by district area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

the coefficients from the lagged estimation of air pollution on crime are presented, the coefficients are small and not statistically different from zero. The coefficient in Column 4 is even negative and it is very imprecisely estimated.

The specifications in Table 5 add other district level controls and rice production related controls into the equation. The dependent variable is log of non-violent annual district crimes. Once again, Columns 3 and 4 present the same specifications as Columns 1 and 2, respectively, for the lagged effect of air pollution on crime. Columns 1 shows a positive and statistically significant effect of air pollution on crime. Compared to Column 1 in Table 4, the coefficient size reduces to about

14 percent. The coefficients in remaining three Columns are not statistically different from zero. Furthermore, the coefficients for the lagged effect of air pollution on non-violent crime are not only negative but are also very imprecisely estimated.

Table 1.5 The effect of air pollution on non-violent crimes (with additional controls).

Log of Annual Non-Violent Crimes per 1000 Sq. Km				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
			Lagged Effects	
AOD_w_{jt} (Standardized)	0.14015*	0.10230	-0.03906	-0.04944
	(0.07247)	(0.07870)	(0.06451)	(0.07421)
Bootstrap P-value	[.06306]	[.23724]	[.67968]	[.52853]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Rice Controls	No	Yes	No	Yes
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Observations	490	428	428	428
R-squared	0.962	0.973	0.979	0.980
Avg. Air Pollution	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801
Avg. Crime	6337	6337	6423	6423

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual non-violent crime in a district weighted by district area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. Columns 1 and 3 include other district level controls and Columns 2 and 4 additionally control for rice production variables. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

The results for the effect of air pollution on non-violent crime suggest two things. First, the results are sensitive to changes in specification, and therefore, not as robust as the the results for the effect of air pollution on violent crimes. Second, there seems to be no lagged effect of air pollution on non-violent crimes.

The second conclusion is in line with the psychological literature on air pollution and aggression. Air pollution affects cognitive performance which leads to reduced thresholds for frustration tolerance (Anderson and Bushman 2002; Rotton 1983; Rotton et al. 1978), and decreases serotonin levels in the body which is linked with increased aggression (Gonzalez-Guevara et al. 2014; Murphy et al. 2011). Reduced cognitive performance is much more likely to increase violent offenses like committing an assault than a non-violent crime like burglary or robbery.

In my data set, some of the non-violent crimes include robbery, burglary, motor vehicle theft and ordinary theft. Successful execution of these crimes must require some use of cognitive ability. Air pollution, meanwhile, is known to reduce cognitive performance. In fact, it is highly likely that crimes like robberies require offenders to make quick decisions and, often times, collaborate with others (Maree 1999). Executing these decisions in real time requires cognitive ability.

On the other hand, the link between cognitive ability and violent crime is totally opposite. There is plenty of existing psychological literature that links reduced cognitive ability to an increase in violent crime. The control theory suggests that a decrease in cognition is linked to decreased self control which then leads to an increased propensity to commit violent crimes (Gottfredson and Hirschi 1990;Pratt and Cullen 200; Vazsonyi et al. 2001; Salmi and Kivivuori 2006). Reduced cognition has also been shown to be linked with reduced empathy which is also linked to an increased tendency to commit a violent offence (Covell and Scalora 2002). There is also evidence that gender differences in development of social cognition explain why men are much more likely to commit violent crimes than women (Bennett et al. 2005).

1.7 Robustness Analysis

In the previous section, I have shown that the results for the violent crimes are robust to employing different specifications as well as adding additional district level time varying control variables. In this section, I would further prove the robustness of the results presented in the previous sections. First, I will provide empirical evidence that links air pollution and fires.

1.7.1 Air Quality and Fires

The discussion in the Background and Empirical Methodology sections establishes that the wind coming in from the 12 rice growing districts does contribute substantially to the air pollution in the Punjab province during the winter months. Here, I provide empirical evidence that the fires burning in the rice growing districts in the months of October to December contribute to the increase in air pollution in the winter months of November, December, January and February.

Therefore, I will now establish that the the fires burning in rice growing districts do indeed increase air pollution. For the estimation linking fires to air pollution, I use the air quality value in the four winter months AOD_w_{jt} as the main outcome of interest. The main explanatory variable of interest is defined as $Fires_t^T$ or the annual number of fires in the months of October, November and December. This term is expected to have a positive sign since an increase in fires should worsen air quality.

I run the following OLS regression equation for this purpose:

$$AOD\_w_{jt} = \alpha_1 Fires_t^T + X_{jt}A + \zeta_j + \zeta_j * t + \psi_{jt} \tag{1.4}$$

where the dependent variable, AOD_w_{jt} is the AOD value in the four winter months. $Fires_t^T$ is the mean number of fires during the months of October to December in the rice growing districts. Since $Fires_t^T$ only varies by year, it is not possible to include time fixed effects. Instead, I include time trend at various levels in different specification. In equation 4, ζ_j are district fixed effects, $\zeta_j * t$ is time trend at an administrative level and ψ_{jt} is the random error term. α_1 is the main coefficient of interest here since it tells us the increase in air pollution due to fires blowing in the rice-growing districts.

In Table 6, the coefficient on α_1 is expected to have a positive sign because an increase in the mean number of annual fires in the rice growing districts should increase air pollution all over the Punjab province. The results from equation 4 are presented in Table 6. As expected, α_1 has a positive sign in all the 3 specifications and it is statistically different from zero in all the specifications. In Column 3, which reports results from the fully specified model, a one standard deviation increase in the number of fires increases air pollution by 0.27 standard deviation. These results add to the evidence that the fires burning in the rice growing districts in the months of October to December do indeed worsen air quality in the whole Punjab province in the four winter months of November, December, January and February.

Table 1.6 The effect of fires on air pollution.

	Average Air Pollution in Winter Months		
	(1)	(2)	(3)
	OLS	OLS	OLS
$Fires_t^T$ (Standardized)	0.22332***	0.26288***	0.27553***
	(0.07061)	(0.08287)	(0.09430)
Bootstrap P-value	[.00100]	[0.0000]	[.00300]
District FE	Yes	Yes	Yes
Time Trend	Yes	No	No
Distric-Specific Trend	No	Yes	Yes
Rice Controls	No	No	Yes
Weather Controls	Yes	Yes	Yes
Observations	612	612	544
R-squared	0.240	0.254	0.231
Avg. Air Pollution	2126	2126	2126
Avg. No. of Fires	76.29	76.29	76.29

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

Notes: The results are from the OLS estimation of equation 1.4. The dependent variable is the average air pollution in months of November, December, January and February. The main explanatory variable of interest, $Fires_t^T$,is standardized. Column 3 includes other district level controls for rice production variables. The data on rice production is not available for 2018. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Since information on the type of fire is not available, I cannot determine whether these fires were coming from rice fields or not. However, I have presented descriptive evidence in the Background section that the number of fires around the rice stubble burning time have increased recently. Besides, the claim that these fires do indeed come from the rice fields is corroborated by the surveys conducted by the FAO (2018). Hence, the fires located in the rice growing districts which occurred during the rice stubble burning time are very likely to come from the rice fields.

To have an effect on the annual crime rate, the increase in air pollution caused by rice stubble burning should be large enough to affect the annual average air pollution. For this purpose, I change the outcome of interest to annual air pollution and estimate the equation 1.4 again. The results are presented in Table 7. The specifications presented in the 3 columns of Table 7 are exactly identical to the 3 specifications presented in Table 6. The interpretation of the coefficients presented in Table 7 is virtually similar to those presented in Table 6.

Table 1.7 The effect of fires on air pollution.

	Average Annual Air Pollution		
	(1)	(2)	(3)
	OLS	OLS	OLS
$Fires_t^T$ (Standardized)	0.41854***	0.41486***	0.43498***
	(0.07332)	(0.08258)	(0.09099)
Bootstrap P-value	[.00000]	[0.0000]	[.00000]
District FE	Yes	Yes	Yes
Time Trend	Yes	No	No
Distric-Specific Trend	No	Yes	Yes
Rice Controls	No	No	Yes
Weather Controls	Yes	Yes	Yes
Observations	612	612	544
R-squared	0.149	0.161	0.175
Avg. Air Pollution	2005	2005	2005
Avg. No. of Fires	76.29	76.29	76.29

Robust standard errors in parentheses

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

Notes: The results are from the OLS estimation of equation 1.4. The dependent variable is the average annual air pollution. The main explanatory variable of interest, $Fires_t^T$,is standardized. Column 3 includes other district level controls for rice production variables. The data on rice production is not available for 2018. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

A similar result was obtained by Rangel and Vogl (2019) who showed that agricultural fires in sugar cane fields in Sao Paolo, Brazil worsen the air quality in the municipalities located upstream of the location of fires. In line with their findings, I also find that fires from rice stubble burning worsen air quality. I cannot classify all the fires as agricultural fires, but the evidence presented in the Background section demonstrates that the increase in the number of fires in the recent years is most likely the result of the growing practice of stubble burning by rice farmers. Regardless of the type of fires, the results in Tables 6 and 7 present strong evidence that fires are linked with increased air pollution.

1.7.2 Weighting Crime by Population instead of Area

The results presented so far weight the number of crimes by the district area per 1,000 square kilometres. Therefore, another concern could be that the estimates presented so far are driven by the weights assigned to the dependent variable through the district area. It does not make sense to use the number of crimes as a dependent variable without any sort of weighting. For instance, a district with a particularly large area size or a large population might have very large number of crimes. Without weighting, this district would be an outlier in the data and it might drive the coefficient estimates.

Hence, a good robustness check would be to weight the crime variable differently. I, therefore, estimate equation 2 using instrumental variable regression again but I weight the number of crimes by the district population per 100,000 people instead. I present the results in Table A8 in the appendix.

I run all the specification presented in Tables 2 and 3 in the discussion section but I only present 4 of them in Table A8 in the appendix. The specification in column 2 adds the division specific time trend, rice production related controls and other district level controls. Columns 3 and 4 have identical specification as Columns 1 and 2 except that they estimate the lagged effect of air pollution on crime. Barring the first specification in Column 1, all other specifications in Table A8 in the appendix report a the coefficient estimate that is statistically different from zero. The coefficient estimates in Table A8 in the appendix are similar to the coefficient estimates presented previously in Tables 2 and 3, in terms of absolute size. In Table A8 in the appendix, Columns 2 and 4 report the fully specified model for current and one-year lagged effects of air pollution on crime and they show a 21.8 percent and 17.5 percent increase, respectively, in crime per 100,000 people due to a one standard deviation increase in air pollution in the 4 winter months.

The results in Table A8 in the appendix make a strong case that the results in the previous section are not driven by the weight assigned to the dependent variable through the district area. Besides, the coefficient estimates after weighting by district population are more or less similar to the previous coefficient estimates, in terms of the coefficient size.

1.7.3 Changing the Instrument to Account for the Base Year Rice Area

The proportion of total area cultivated with rice belonging to the 12 major rice growing districts plays an important role in determining the amount of air pollution that the Punjab province endures in the winter months. While -in the construction of the instrument- I have accounted for the wind direction, the position of the district with respect to the wind direction and the distance of a district from the rice growing districts, I have not accounted for the proportion of area allocated to rice production in the 12 rice growing districts relative to the total area allocated to rice production in the Punjab province.

Annual district rice area is linked with district's economic activity, agricultural production and other climatic factors. Hence, it fails to satisfy the exogeneity condition and it cannot be directly included in the construction of the instrument. However, a Bartik instrument can be constructed which has been used extensively in the literature. I follow Duflo and Pandey (2007) in my construction of the instrument here which is only a slight variation of the instrument discussed before and used in equation 2. I multiply the total area sown with rice in the Punjab province each year with "the proportion of area sown with rice in the rice growing districts in the base year" [35]. This gives the predicted area sown with rice each year in the 12 major rice growing districts. Since this is the predicted area, it is uncorrelated with the outcome of interest by construction. Next, I weight the instrument discussed before by the inverse of the predicted area.

[35] Following Duflo and Pandey (2007), a base year is defined as the year before the recent escalation of the rice stubble burning practice. I take the earliest possible year for this purpose which is 2002.

Before discussing the results from the instrumental variable estimation of equation 1, it is important to discuss the first stage results because the instrument has essentially changed now. In Table B1 of Appendix B, I present the first stage results from the estimation of equation 2 with this new instrument discussed above. Column 1 only includes district fixed effects and time fixed effects while Column 2 also includes division specific time trend. Columns 3 and 4 present the first stage results from same specifications as Columns 1 and 2 respectively, but from the IV regression estimation of crime on one-year lagged air pollution.

The first stage F-stat improves with this modified instrument. The lowest value the first stage F-stat takes is 19.49 in Column 2 of Table B1 in the appendix which includes all the fixed effects and time trend. However, I have not used this instrument in my main specifications earlier because I do not have a clear base year defined. While the FAO's (2018) report does tell us that the rice stubble burning practice increased exponentially around 2015 and this is corroborated by the newspaper articles in the media, the practice of rice stubble burning still existed before 2015. It is also not possible to get an idea of “by how much did the stubble burning increase after 2015".

Next, I present the results from the instrumental variables estimation of equation 1 with this amended instrument. I present the results in Table 8. The dependent variable is the log of violent annual crimes in each district weighted by the district area. Compared to Table 2 in the Results section, nothing changes in terms of interpretation. As in Table 2, air pollution tends to have a more robust effect on the one-year lagged violent crime. The coefficients are also in the ball-park of those estimated in Table 2. Column 4 is the fully specified specification in this case, for lagged effect of air pollution on crime. The coefficient in Column 4 of Table 8 shows that a one standard deviation increase in air pollution increases violent crime by about 21.2 percent.

This variation of the instrument serves as an important robustness check for both the first stage results and the main equation estimation results. It lends more weight to the claim that the fires burnt in the rice field for clearing rice stubble do indeed increase air pollution in all the districts of the Punjab province. The increase in air pollution levels then leads to an increase in the violent criminal activity.

Table 1.8 Main estimation equation results with the modified instrument.

Log of Violent Annual Crimes per 1000 Sq. Km				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
			Lagged Effects	
AOD_w_{jt} (Standardized)	0.21361**	0.15150	0.24904***	0.21203**
	(0.10685)	(0.09760)	(0.08112)	(0.08324)
Bootstrap P-value	[.03103]	[.20821]	[.00601]	[.01401]
Observations	611	611	575	574
R-squared	0.905	0.918	0.907	0.922
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Rice Controls	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No
Avg. Air Pollution	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801
Avg. Crime	549.5	549.5	550.4	550.4

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

Notes: The results are from the instrumental variable estimation of equation 1.1. For building the instrument, the instrument already used in equation 1.2 is weighted by the inverse of the predicted rice area. The dependent variable is the log of annual violent crime in a district weighted by district area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

1.7.4 Classification of Rice Growing Districts

As discussed in the Background and Data sections, I classified 12 out of 36 districts as rice growing districts in Punjab. I used the data on rice production from 2002 to 2017 for this purpose. I defined rice growing districts as those whose production is greater than the 75^{th} percentile of total rice production for at least 10 years. One threat to identification could be that the results are susceptible to the classification of rice growing districts.

My definition of rice growing districts is fairly robust as long as I use the 75^{th} percentile as the threshold for defining rice growing districts. The 12 districts classified as rice growing districts do not change if I use area sown with rice instead of rice production as the classification variable. The classification of these 12 districts also does not change if I create the percentiles without grouping the data by year -this holds regardless of whether I use rice production or area sown with rice.

Furthermore, changing the 75^{th} percentile threshold also does not make sense. Increasing it to, let's say 90^{th} percentile leaves only 4 districts that can be classified as rice growing districts. This would mean that the analysis fails to account for the air pollution from the fires clearing the rice stubble in 8 other districts which lead in rice production. On the other hand, decreasing the threshold to, let's say 50^{th} percentile leads to 23 out of 36 districts being classified as rice growing districts. This threshold is too low and may lead to a weak instrument because of inadequate smoke being produced during the residue burning season, in the relatively smaller rice growing districts.

Therefore, I use the classification of rice growing districts used by FAO (2018) as a robustness check. I define the 11 districts -where FAO conducted surveys with the rice farmers- as the rice growing districts. The remaining construction of the instrument remains same as defined in the Empirical Methodology section. I present the results from the IV estimation of equation 2 in Table A9 in the appendix.

First, there is little to no change in the first stage F-stat when the definition of rice growing districts is changed [36]. Second, the 4 specifications presented in Table A9 in the appendix which are identical to the 4 specifications presented in Table 2 earlier in the Results section. The dependent variable is the log of violent annual crimes in each district weighted by the district area. The coefficient estimates in Table A9 in the appendix are comparable to the estimates in Tables 2 and 3 in the Results section, in terms of absolute size. Columns 1 and 2 in Table A9 in the appendix show show a 25.8 and 18.7 percent increase in crime, respectively, due to a one standard deviation increase in air pollution, respectively. Columns 3 and 4 presented the same specifications as Columns 1 and 2 but for the lagged effect of air pollution on crime. As in Column 2 of Table 2, the coefficient in Column 2 of Table A9 in the appendix is not statistically different from zero. The specification in Column 4 is the fully specified model which reports a 25.7 percent increase in

[36] These first stage regression results are not presented here but they are available with the author.

crime due to a one standard deviation increase in air pollution in the previous year.

The coefficient sizes differ only slightly in absolute size when the definition of rice growing districts is changed. My classification of rice growing districts had only 3 different districts from FAO's (2018) classification of rice growing districts. Hence, as long as all the major rice growing districts are identified correctly, the results are robust to the change in the classification of rice growing districts.

1.7.5 Constructing the Instrument and Endogenous Variable for the Same Months

One threat to identification is that the results obtained from the construction of the main predictor variable and the instrument are just a fluke. This concern can arise because the instrument considers wind direction for the months October, November and December while the air pollution is considered for the months November, December, January and February.

To alleviate this concern, I define the instrument and the air pollution for the same months. Specifically, the instrument is now constructed using the months October, November, December, January and February. The air pollution variable is also the mean daily AOD value for these 5 months. I present the results in Table 9. The dependent variable is the log of violent annual crimes in each district, weighted by the district area. The specifications in Table 9 are comparable to the 4 specifications in Table 2 in the Results section. Column 2 adds the division specific time trend while Columns 3 and 4 run the same specifications to estimate the lagged effect of air pollution on crime.

First, there is little to no change in the first stage F-stat when the number of months used to construct the instrument is changed [37]. Second, the results in Table 9 suggest that there is no major change in the interpretation of the main results. Previously, the coefficient estimates for the lagged effect on crime were more robust to changes in specification. With this specification, the lagged effect estimates seem to be more sensitive to changes in specification than the contemporaneous effect of air pollution on crime.

[37] These first stage regression results are not presented here but they are available with the author.

Nonetheless, in terms of the absolute size, the coefficients are in the ball park of estimates presented in Table 2 in the Results section. A one standard deviation increases violent crime by about 25.8 percent in Column 1 of Table 9. This is slightly larger than the estimate from the similar specification in Table 2 -the coefficient size was about 21.4 percent from the same specification in Table 2. The results in Table 9 give credence to the claim that my main Results are indeed causal and are not affected by the way the instrument and the air pollution variables are constructed for the main analysis.

Table 1.9 Main estimation equation results with instrument and endogenous variable constructed for the same months

Log of Violent Annual Crimes per 1000 Sq. Km				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
			Lagged Effects	
AOD_w_{jt} (Standardized)	0.25837**	0.18742	0.29541***	0.25773**
	(0.13813)	(0.15213)	(0.11514)	(0.12171)
Bootstrap P-value	[.04605]	[.24725]	[.00400]	[.01301]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Rice Controls	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No
Observations	611	611	575	574
R-squared	0.892	0.913	0.913	0.933
Avg. Air Pollution	2332	2332	2332	2332
Avg. Area(2017)	5801	5801	5801	5801
Avg. Crime	549.5	549.5	550.4	550.4

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual violent crime in a district weighted by district area. The main explanatory variable is the average air pollution in months of October, November, December, January and February. The instrument is the wind direction -as explained in the paper- but for all the 5 months for which air pollution is considered. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

1.7.6 Placebo Test

The spatial setting of the context allows me to check for a placebo test. As discussed in figure 2, the rice growing districts are located in the Eastern part of the Punjab province. Meanwhile, the wind direction during the time of stubble burning takes wind to the North and North-West of the rice growing districts. If this is to hold true, then wind direction from the Western most districts of the Punjab province should not blow towards the other districts in the province. Hence, it should have no effect on air pollution. Besides, these districts are not rice growers and therefore, they should not be a major contributor to the air pollution problem in the winter months. Hence, treating these districts as rice growers should not be a good identification strategy for estimating the impact of air pollution on crime.

To test this, I assume the districts located in the Western part of the Punjab province as rice growing districts. These are districts that are neither actual rice growing districts nor their neighboring districts. If the wind is blowing to the North and North-West, then the wind direction from these districts should not have any impact on the air pollution. I estimate the equation 1 with this classification of rice growing districts.

I present the results in Table B2 in the appendix. It contains the results from the first stage estimation as well. The 4 specifications are once again comparable to the specifications presented in Table 2 in the Results section. For the first stage estimation results, the coefficient is infinitesimally small and closer to zero. The first stage F-stat is well below 10 in all the 4 specifications in Table B2 in the appendix. This gives strong evidence that the instrument is a weak instrument. Because of the weak instrument problem, the coefficients from the main estimation equation for AOD_w_{jt} are very high in magnitude, although none of them is statistically different from zero.

1.8 Heterogeneity Analysis

In this section, I will briefly consider different types of crimes individually instead of aggregating them into violent and non-violent crimes. The violent crimes considered below include attempted murder, assault, kidnapping, murder and rape. The non-violent crimes considered below include motor vehicle theft, dacoity, robbery, ordinary theft and burglary.

Given the results obtained and discussed earlier, I expect a larger and robust increase in violent crimes compared to the non-violent crimes. In Table B3 in the appendix, I present the results from the instrumental variable estimation of equation 1 for 5 types of violent crimes. All the coefficients are for the effect of air pollution on crime in the contemporaneous year. Each column presents the results for a specific type of a violent offense. The dependent variable is log of the crime type weighted by district area per 1,000 square km.

The largest coefficient is for the rape offense in Column 5, a one standard deviation increase in air pollution leads to a 41.8 percent increase in rape crimes. Given the magnitude of the coefficient for increase in rape offenses and the grave nature of the crime, it entails more discussion. Rape crimes tend to be under reported in most of the third world. More importantly, they are known to affect the well being of the victim. In the contemporary world, rape crimes have serious consequences in most legal and social structures. Many countries have developed laws that require employers to provide Relationship, Violence and Sexual Misconduct (RVSM) training, enact policies for dealing with the offenders and outlining a procedure for dealing with such occurrences. A 41.8 percent increase in rape crimes puts a dent in the efforts to curb rape offenses. In developing countries, victims often lack adequate legal support and an enabling environment which inhibits their ability to cope and their efforts to pursue legal justice.

Table B3 in the appendix also shows that, other than Kidnapping, all other violent crimes have a positive and statistically significant coefficient. The smallest coefficient is for assaults, a one standard deviation increase in air pollution leads to an 18.6 percent increase in assault offenses.

In Table B4 in the appendix, I repeat this exercise for one year lagged effect of air pollution on crime. Once again, all violent crimes other than kidnapping have a positive and statistically significant effect on crime. The largest coefficient is for murder offenses, a one standard deviation increase in air pollution leads to a 30.2 percent increase in murders. The coefficient on rape offenses shows a 24.3 percent increase due to a one standard deviation increase in air pollution; this is still a very big coefficient in terms of its practical significance but it is much smaller than the coefficient for contemporaneous increase in crime shown in Column 5 of Table B3 in the appendix.

Next, I conduct the same exercise for non-violent crimes. I present the results in Table B5 in the appendix. All the coefficients are for the effect of air pollution on crime in the contemporaneous year. Each of the 5 Columns presents the results for a specific type of a non-violent offense. The dependent variable is log of the crime type weighted by district area per 1,000 square km.

The coefficients in Table B5 in the appendix for the 5 non-violent crimes are smaller than the coefficients for the violent crimes in Table B3 in the appendix. Only the coefficient on ordinary theft is statistically different from zero and it is also the largest in terms of absolute size. A one standard deviation increase in air pollution increases ordinary thefts by about 24.4 percent. All other coefficients are much smaller and not statistically different from zero.

Overall, the heterogeneity analysis adds to the story that violent crimes are more likely to increase due to air pollution, than non-violent crimes. Throughout the evidence presented in the last three sections, it can be seen that air pollution has a larger effect on violent crime. This effect also tends to linger on for an additional year through air pollution's lagged effect on crime -though this might be because of the timing of the increase in air pollution. For non-violent crimes however, the effect is smaller in magnitude and it is sensitive to changes in specification. It is also only present in the contemporaneous year [38]. In the next section, I will discuss the channels that can help us understand why air pollution leads to an increase in crime.

1.9 Mechanisms

The labor market shocks caused by extreme levels of air pollution can be a potential channel that help us understand the link between air pollution and crime. Literature has shown that air pollution affects cognitive performance, productivity and labor market participation (Wangyang et al. 2021; Archsmith et al. 2018; Hanna and Oliva 2015; Lavy et al. 2014; Stafford 2014; Zivin and Neidell 2012; Zivin and Neidell 2009).

There is substantial literature on the link between labor market opportunities and crime. The

[38] The results for the non-violent crimes in the Robustness section have not been presented in the paper. However, they are available with the author.

latest piece of evidence adds to this literature by showing that seasonal increases in labor demand in the agricultural sector during the time of harvest reduce incentives to commit crime (Charlton et al. 2021). It is well documented in the literature that highly uneducated and poor male individuals are more likely to indulge in criminal offenses (Campaniello and Gavrilova 2018; Kelly 2000; Lochner and Moretti 2004). Women tend to respond less to incentives such as illegal earnings than men do (Campaniello and Gavrilova 2018), inequality is more likely to increase violent crime while poverty is associated with property crime (Kelly 2000).

A great deal of literature also explores the association between changes in opportunities available in the labor market and criminal activity. Blakeslee and Fishman (2018) find that weather related income shocks drive criminal behavior in India. Availability of additional income through transfer programs such as the SNAP distribution program lead to a considerable reduction in crime (Carr and Packham 2019). Equality of new opportunities also matters because criminal activity increases in local neighborhoods where only a fraction of residents experience an increase in earnings (Freedman and Owens 2016). There is also a clear causal relationship between wages and crime, and unemployment and crime (Gould et al. 2002; Lin 2008). Increases in earnings and employment opportunities both have a negative relationship with criminal activity. Gould et al. (2002) found that wages tend to have a stronger relationship with crime than unemployment while Lin (2008) found that a 1 percent point increase in unemployment in the United States led to a 1.8 percent increase in property crime. This is substantiated by the research that teenagers not participating in the labor market are more criminal than the teenagers active in the labor market (Llad et al. 1972).

Psychological literature can also help us understand the link between air pollution and crime. Here, I provide a brief discussion of the models from psychology and criminology that help develop a better understanding of how air pollution may impact crime, and in particular, violent crime. I discuss two hypothesis, namely “Frustration-Aggression Hypothesis" and the “General Strain Theory".

Frustration-aggression hypothesis defines frustration as an obstacle to a certain achievement. Berkowitz (1989) modifies the original hypothesis to develop a multi-stage causal pathway. The starting point is a frustration that leads to a negative emotional response that leads to an aggressive inclination which can potentially result in an aggressive act in the form of a violent crime. Air pollution has been shown to increase frustration (Rotton 1983; Rotton et al. 1978) so it can, indeed, lead to an increase in violent crime.

General strain theory is rooted in criminology but it has a large degree of overlap with the frustration aggression hypothesis (Giulietti and McConnell 2020). A strain in this theory is broadly defined as either (i) the failure to achieve positive goals, (ii) the removal of positively valued stimuli from life, or (iii) the presence of negative stimuli (Agnew 2001). Air pollution is known to increase suicide attempts, depression and psychiatric admission rates which suggests that sir pollution can increase the strain as defined in the general stress theory. Agnew (2001) characterizes a strain high in magnitude as a precursor to increase in violent crimes.

The control theory suggests that decreased self control can lead to an increased propensity to commit violent crimes (Gottfredson aand Hirschi 1990). There are various versions of this theory. For instance, the social control theory suggests that the stronger an individual's bonds to the society the less likely they are to commit a crime.

This literature can also help us understand how labor market shocks can increase crime. Unable to find work can be a failure to achieve a positive goal which can increase the tendency to be violent, as per the general strain theory. Decreased earnings or being unemployed can increase frustration levels thus, increasing the tendency to be aggressive. Under the dynamics of control theory, unemployed individuals may also lose their bonds with the society which can increase their likelihood to be deviant.

Other work in psychology is also relevant for this context. Reduced cognition has also been shown to be linked with reduced empathy which is also linked to an increased tendency to commit a violent offence (Covell and Scalora 2002). There is also evidence that gender differences in development of social cognition explain why men are much more likely to commit violent crimes than women (Bennett et al. 2005).

Pakistan is a lower middle income country with about 75% of its labor force being male. In

2017, Pakistan's literacy rate stood at about 59% and its unemployment rate was about 3.95%. It also has a youth bulge in it's demographic structure, with more than 60 percent of the population aged 35 or below. As noted above, all these factors are associated with criminal activity.

As discussed above, changes in labor market opportunities and labor market shocks are one of the most important drivers of criminal activity. A decrease in earnings or a decrease in employment opportunities can increase criminal activity. Air pollution is known to affect labor market outcomes. It can create an economic incentive to supplement income through illegal income. Besides, taking the general strain theory from psychological literature into account, the failure to achieve the goal of being employed can increase frustration and unhappiness in everyday life which could then lead to an increased likelihood to commit a criminal offense. Being unable to find work can also weaken an individual's internalization into the society which, following the control theory, can increase the likelihood of deviance.

To test these hypothesis, I use data from the socioeconomic surveys on information about individual level labor market outcomes. I hypothesize that a decrease in labor market opportunities for older male workers, due to air pollution, can be an important link between crime and air pollution.

Due to the seasonal nature of air pollution however, the labor market effects can be seasonal in nature as well. For instance, it is possible that unemployment rate increases in a certain month due to air pollution but moves back to the baseline rate later. This would mean that aggregated data at annual level would not reveal any seasonal variations in the unemployment rate, suggesting no change in annual unemployment due to air pollution.

The information on individual labor market outcomes such as employment status and income levels comes from two surveys, namely Pakistan Living Standards Measurement Survey (PSLMS) and Household Income and Expenditure Survey (HIES). The information on the timing of the survey is available in both the data sources. I exploit the information on the month in which a household was surveyed. This approach helps identify the effect of air pollution on the outcome variable of interest in the 4 winter months relative to the rest of the year. I run the following variation of equation 1 for this purpose:

$$log(Y_{ijt}) = \rho_1 1^S[AOD\_w_{jt}] + \rho_2 S + X_{ijt}P + \tau_t + \upsilon_j + \vartheta_k * t + \chi_{ijt} \tag{1.5}$$

where Y_{ijt} is the outcome of interest for individual i whose sex is male, in district j in year t. 1^S is an indicator function that equals 1 for all individuals observed in the months of November, December, January and February. AOD_w_{jt} is the normalized value of Aerosol Optical Depth (AOD) in the four winter months. X is a vector of controls similar to the one used in previous equations and additionally includes years of education and age of each observed individual, τ_t are year fixed effects, υ_j are district fixed effects, $\vartheta_k * t$ is division specific time trend and χ_{ijt} is the random error term.

In Table 10, I present the results with log of monthly cash income as the main outcome of interest [39]. Only male individuals are considered. Column 1 presents the results for individuals aged between 23 and 30 [40], and Columns 2, 3 and 4 present the results for individuals aged between 30 and 40, 40 and 50, and 50 and 60 respectively.

Literature suggests that younger male individuals are more likely to be deviant. However, youngest members of the workforce are also more likely to be healthier. The middle aged workers and older workers are likely to suffer the most because of air pollution through its affects on health and on their productivity. Conditional on suffering a labor market shock, the middle aged workers will be more likely to commit a crime because of their better physical ability and because of being under pressure to provide for the family. I will discuss this in more detail later.

The coefficient in Columns 1 and 2 is negative but it is statistically not different from zero. The coefficient in Column 3, however is negative and statistically different from zero. Using the bootstrap p-value for inference, it is also statistically different from zero at 90% significance level.

[39] I adjust for the one month lag in the observation of the individual relative to the unemployment time in the regressions.

[40] Individuals below 23 years of age are not included. 23 is the average age of completing 16 years of education in my data. For individuals aged below 23, more capable ones may decide to go to college instead of opting work, and thus, may not be the part of the labor force. This can lead to selection issues where more able individuals opt out of the labor market.

Table 1.10 Income shock for older males as a potential mechanism.

	Log of Real Monthly Cash Income of Males			
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
	23 < Age ≤ 30	30 < Age ≤ 40	40 < Age ≤ 50	50 < Age≤ 60
AOD_w_{jt} (Standardized)	0.22392	0.41821	-0.14224*	-0.11230
	(0.24105)	(0.59247)	(0.11324)	(0.29318)
Bootstrap P-value	[.22623]	[.44745]	[.08509]	[.61862]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Observations	36,226	41,720	38,154	17,674
R-squared	0.443	0.387	0.475	0.496
Avg. Air Pollution	2311	2311	2311	2311

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

Notes: The results are from the instrumental variable estimation of equation 1.5. The dependent variable is the log of monthly cash income. The main explanatory variable of interest, AOD_w_{jt},is standardized. The instrument is the wind direction -as explained in the paper. The explanatory variable is the interaction of the air pollution variable with a dummy that equals 1 for the four winter months. Only male individuals are considered. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

The coefficient shows a 14.24 percent decrease in earnings for male individuals aged between 40 and 50, due to one standard deviation increase in air pollution [41]. The coefficient for male individuals aged between 50 and 60 is also negative but it is imprecisely estimated.

Air pollution decreases incomes in the four winter months for the middle aged male members of the labor force. The paucity of data does not allow me to understand if the changes are due to a labor demand shock or a labor supply shock. One possibility is that there is a labor supply shock since air pollution is known to affect labor productivity (Zivin and Neidell 2012). This explanation makes sense since older and middle-aged members of the labor force are likely to be less healthier than younger members of the labor force and thus, are more susceptible to the

[41] If I instead use the standard errors only clustered by district -which may not be correct for inference- the coefficient is just marginally insignificant at 90% significance level.

cognitive and health related effects of air pollution. Thus, the productivity of the older workers is affected disproportionately more than the productivity of younger workers.

It is also not surprising that the workers in the youngest age category do not experience any change in their income levels. On average, these individuals are likely to be the healthiest members of the labor force. In other words, air pollution is the least likely to impact the productivity of the male workers younger than 40. The middle age workers on the other hand are not only more likely to have an existing medical condition but are also more vulnerable to exposure to pollution.

Another important consideration here is that male household heads are often the sole bread-winners in the house. In my data, women only form about 20% of the labor force in Pakistan and majority of the middle aged women are home makers. Hence, the opportunity cost of decreased earnings for middle aged men is higher because of the pressure to provide livelihood and to sustain the family. Coupled with the psychological mechanisms discussed earlier, this phenomenon perhaps helps explain the high increase in violent crime.

Specifically, the general strain theory helps pin point that suppressed earnings among middle aged male individual can channel increased frustration levels due to his failure to achieve his positive goals of earning like others and sustaining his family. This can translate into an increase in the tendency to be violent (Agnew 2000).

To firmly establish the claim that middle aged male workers commit more crime due to air pollution, empirical evidence is needed on whether air pollution increases criminal activity among middle aged men. However, I do not have data on crime statistics by age groups which prevents me from exploring this further. Instead, I turn to the literature on air pollution and crime to strengthen the validity of this mechanism. Burkhardt et al. (2019) find that the relationship between air pollution and violent crimes is stronger in US counties with older populations. Specifically, they find strong statistical differences across age brackets, and counties with higher median age brackets have a stronger association between air pollution and crime.

Weak evidence in support of the mechanism discussed above also comes from research in UK which found that while male offenders are more likely to commit crime due to higher carbon monoxide levels, age of the criminal offender is not related with the likelihood to commit violence due to pollution (Cruz et al. 2021). This is contrary to the general relationship between criminal offense and age which tends to be negative. Overall, research suggests that the relationship between air pollution and criminal activity is not mediated by age. Instead, it may be aggravated by age, as found by Burkhardt et al. (2019).

An associated concern could be that the decrease in seasonal earnings is driven by trends in employment. A seasonal decrease in labor demand can, for instance, increase unemployment and suppress earnings. An increase in unemployment can therefore confound the interpretation by suggesting that the decrease in income levels is associated with the seasonal slow down in economic activity.

In Table B6 in the appendix, the dependent variable equals 1 if an individual is unemployed. I report the estimates from instrumental variable regression of equation 5. I run the same estimations as those presented in Table 10. Only male individuals are considered. Column 1 presents the results for individuals aged between 23 and 30, and Columns 2, 3 and 4 present the results for individuals aged between 30 and 40, 40 and 50, and 50 and 60 respectively.

Only the coefficient for male workers aged between 40 and 50 is positive, and it is very imprecisely estimated. The coefficient for all other age groups is negative. The coefficient for the individuals aged between 23 and 30 is statistically different from zero if I use the bootstrapped p-values for inference. This makes sense since these are the youngest members of the labor force whose health and productivity is likely to be least impacted by air pollution. Furthermore, since this age group does not experience a decrease in earnings due to air pollution, the reduction in unemployment for this age group does not suggest a seasonal decrease in labor market activity. Thus,the results reported in Table B6 in the appendix seem to suggest that the decrease in earnings of middle aged workers discussed above is the labor market shock that is driving the association between air pollution and crime [42].

Next, I will briefly discuss the psychological mechanisms that can lead to an increased tendency

[42] I do not have enough information in the data to conclude if it's a demand side or a supply side shock.

to be violent. Earlier in this section, I discussed frustration-aggression hypothesis and general strain theory as two theories rooted in psychology and criminology that might help explain the increase in violent crime due to air pollution.

Under these theories, empirically establishing this link will require evidence linking increased air pollution to individual emotional response and the propensity to achieve positively valued goals. Ideally, survey data on psychological well being of individuals and/or on the neurological illnesses will explain an important pathway that leads to increased crime. Unfortunately, to the best of my knowledge, no such data is available that spans the 36 districts of Punjab province considered in this paper.

The Multiple Indicator Cluster Survey (MICS) for the year 2017-18 does provide information on married male respondents about their attitude on domestic violence. Unfortunately, the previous rounds of MICS do not contain this information for male individuals. The questions construct various scenarios and ask if domestic violence towards wife is justified in some scenarios [43]. I combine all the questions to generate one variable that equals 1 if domestic violence towards the wife is justified in at least one of the scenarios.

I present the results with this outcome variable in Table B7 in the appendix. Since the data is only available for a single round, the power for the regression is likely to be very low and the coefficients are very imprecisely estimated. The evidence from the results in Table 16 is mixed and does not provide any conclusive evidence on whether air pollution affects the tendency to justify domestic violence by men towards their spouses.

Nonetheless, the literature does establish that increased air pollution levels can lead to inflammation of nerve tissues which is linked to aggressive behavior (Anderson and Bushman 2002), reduced cognitive performance and reduced tolerance for frustration (Rotton 1983; Rotton et al. 1978). Furthermore, air pollution may directly affect brain chemistry by causing fluctuations in the serotonin levels in the bloodstream (Gonzalez-Guevara et al. 2014; Murphy et al. 2011) which are associated with increased aggression (Coccaro et al. 2011).

[43] Examples of scenarios include whether beating is justified if the wife goes out without husband's permission, does not cook food for the house, takes decisions without consulting the husband etc.

Herrnstadt et al. (2020) also find that air pollution causes an increase in the violent crimes in Chicago but does not have a significant impact on property crimes there. Lu et al. (2018) also find that the increase in crime and unethical behavior due to air pollution is mediated by anxiety. The results presented earlier in the Results section also point towards the likelihood that air pollution is likely to have a greater effect on violent crimes than non-violent crimes. The effect on violent crime is not only more robust to changes in specifications but also tends to hold for another year.

However, these results do not lead to the conclusion that air pollution affects the violent and non-violent crimes equally or through similar channels. Unfortunately, the paucity of data does not allow me to directly estimate the effect of psychological factors on violent crime. Nonetheless, my results do suggest that psychological channels have a much smaller impact on non-violent crimes than on violent crimes.

1.10 Policy Implications

In this section, I use some back of the envelope calculations to estimate the crime costs generated by the increase in air pollution. While this estimate is for the whole Punjab province and does not consider the variation in pollution exposure across different locations, it gives a ball park estimate of the costs of increased crime for a developing country.

Typically, estimates of crime costs for different crime types are used for this purpose. Herrnstadt et al. (2020) use the cost of assault, rape and murder crimes to estimate the additional cost to the society of the increase in crime due to pollution exposure. Studies on mortality use the Value of Statistical Life (VSL) to estimate the cost of lives lost due to a certain negative shock. Unfortunately, these estimates are not available for Pakistan. I use an alternative methodology that has been used in the literature that estimates value of statistical life (Ostro 1994; Quah and Boon 2003; Yaduma et al. 2012).

This method is called the value transfer method that calibrates an estimate from a developed country based on the income differences between the country for which the estimate is available and that in which the estimate is transferred. Almost all the health and economic cost studies conducted in developing countries have employed this technique (Yaduma et al. 2012). Suppose if the VSL for Pakistan is calculated using the VSL estimates in the United States. This technique obtains a VSL estimate for Pakistan using the following equation:

$$VSL_{Pakistan} = VSL_{USA} * (\frac{Y_{Pakistan}}{Y_{USA}})^e$$

where $VSL_{Pakistan}$ is Pakistan's VSL to be estimated via calibration with that of United States VSL_{USA}. is $Y_{Pakistan}/Y_{USA}$ is the ratio of purchasing power parity (PPP) of Pakistan's Gross National Income (GNI) per capital to that of the USA, and e is the elasticity of willingness to pay for a marginal reduction in mortal risk with respect to income. This elasticity is assumed to be 1 in most empirical studies on developing countries (Yaduma et al. 2012).

Following this approach, I calibrate the costs of murder, assault and rape for Pakistan using those from United States as reported in McCollister et al. (2010). Using the 2010 prices and the data from World Bank I calibrate these costs for Pakistan. Next, I calculate the increase in cost of crime for Pakistan using the calibrated calculations for the cost of crimes. In Column 1 of Table 2, I estimated a 21.4 percent increase in crime due to a one standard deviation increase in crime. In the next step, I calculate the average increase in air pollution after 2015 over the air pollution levels in the base year in my data which is 2002. Relative to the air pollution data used for estimations in this paper, it comes out to about a 0.55 standard deviation increase in air pollution.

On the basis of the violent crimes committed in all of Punjab province after 2014, this translates to an increase in violent crimes by about 11.64% due to a 0.55 standard deviation increase in air pollution. The least costly crime is assault. Assuming all the crimes to cost the same as an assault, the cost of crimes to Pakistan is about 497 million US dollars. However, as is the case with transferring estimates for Value of Statistical Life (VOSL) from developing to developed countries, this estimate is likely to be highly overestimated.

To deal with this issue, I first calculate VOSL for Pakistan using VOSL estimates from both United States and India. India is Pakistan's Eastern neighbor and shares similar socioeconomic characteristics to a great extent. I find that VOSL estimates for Pakistan from United States and India differ by a magnitude of 97. Assuming the difference in costs of assault is also on a similar magnitude, I obtain an estimate for cost of crime for Pakistan to be around 5.1 million US dollars. This is a lower bound estimate for the cost of crime given that assault has the lowest costs associated with it. The actual costs are likely to be much higher because the cost of murder tends to be enormous (McCollister et al. 2010).

Since 5.1 million US dollars seems to be a very conservative estimate, I instead estimate the costs of murder, rape and assault crimes separately, and then divide them by 97. Altogether, the additional cost of these crimes caused by air pollution comes to a whopping 600 million US dollars. However, this is driven by the very high cost of murder. The real estimate will most likely be somewhere between 5 million and 600 million US dollars.

1.11 Conclusion

In this study, I considered the agricultural biomass burning in the form of rice residue as an exogenous shock to the air pollution levels. I considered the impact of increased smog levels due to rice residue burning on criminal activity. I found that high levels of air pollution do lead to a significant increase in violent crime. There is some evidence of increase in non-violent crime as well -albeit it being more sensitive to changes in specifications.

I used an instrumental variable approach as the main identification strategy in this paper. Besides a robust and strong first stage, the identification strategy is substantiated by various robustness checks, as well as by placebo tests. The main equation estimates are robust to various different specifications. In line with the findings in the literature, I find air pollution to be an important determinant of crime. Additionally, I find that air pollution raises criminal activity in not just metropolitan cities but in a diverse range of settings from rural to urban regions.

I also make an attempt to understand the channels that drive the association between air pollution and crime. In this regard, I explore evidence on labor market outcomes, health expenditure and attitude towards domestic violence. I find that labor market shocks are an important mechanism. This claim is strengthened by the vastly documented evidence in the literature on the link between labor market shocks and criminal activity.

The results presented above demonstrate that there is a substantial rise in criminal activity when high levels of air pollution are considered. They highlight the social costs of air pollution. Criminal activity can be considered as an important social cost resulting from air pollution in both developed and developing countries.

More importantly, this paper adds to the evidence that curbing air pollution can help reduce crime. This is a more efficient solution for developing countries which lack resources for investment in efforts required to curb crime such as patrolling vehicles, training of police offers and prosecution of criminal offenders. Besides, inability to strengthen institutional capacity, developing countries also have corrupt and inefficient law enforcement institutions which function sub-optimally.

Hence, it can be suggested that the estimates of marginal social costs may be higher than previously considered. This is particularly true for developing countries who lack the legislative framework and the institutional capacity to implement measures that can help bring air pollution to socially optimum levels. Hence, there is a need to prioritize policy making in the developing countries that focuses on the environmental consequences of agriculture, such as burned biomass, and comes up with innovative incentives for the farmers so that the social costs of these activities to the society can be reduced.

This study also emphasizes the fact that agricultural activities have consequences for the environment which in turn creates social costs for the society. Hence, future research work could focus more on estimating the social costs or the negative externalities of agricultural practices in the developing countries. Research can also focus on estimating the impact of alternative agricultural practices that reduce the contribution of agriculture to burned biomass.

Last, this study has significant implications for those developing countries whose economies rely on agriculture. It is important for these countries to adopt and spread practices that come under the ambit of sustainable agriculture. It cannot be stressed further that the social costs of externalities from agricultural sector are much larger than those previously considered. It is difficult to regulate the use of environmentally damaging practices when the crop is a major foreign exchange earner.

It is therefore important to incentivize the use of sustainable agricultural practices.

My finding of a causal relationship between pollution and crime has some clear policy implications. First, the results contribute to the growing evidence that air pollution affects cognitive performance and behavior in ways that have not been considered in most of the literature. Second, the externalities associated with air pollution and environmentally degrading agricultural activities are significantly higher, or the marginal social cost associated with these activities is likely to be much higher than previously thought. Third, it is clear that some agricultural activities have consequences that have not been considered in the literature previously and environmentally damaging agricultural activities have an adverse effect on societal welfare that extend more widely than previously considered. Last, my finding accentuates the need to come up with policy designs that can help developing countries reduce the externalities associated with air pollution and environmentally degrading agricultural activities.

CHAPTER 2

DOES VIOLENCE IN NON-WAR ZONES IMPACT LABOR MARKET OUTCOMES?

2.1 Introduction

There has been a great research interest in the socio-economic impacts of conflicts, violence and wars. However, this research has mostly been focused on former active war zones such as Vietnam (Miguel and Roland 2011; Singhal 2018; Dell and Querubin 2017) and in areas which have experienced persistent civil conflict such as Peru, Colombia and Guatemala (Galdo 2013; Leon 2012; Duque 2017; Chamarbagwala and Morán 2011; Abadie and Gardeazabal 2003). Terrorism, however, has become commonplace beyond the conventional wars and conflicts. It also impacts regions which are not part of an active war or conflict. Little is known about how violence perpetuated by non-state actors in non-war zones impacts socioeconomic outcomes. This paper focuses on changes in the contemporaneous labor market outcomes due to violence in non-war zones.

Terrorism has risen precipitously around the world since the turn of the century in conflict ridden areas. Terrorism related violence has consequences for safety of human life, living standards, infrastructure, economic activity, employment, incomes, health and education. In other words, terrorist attacks can be analyzed as a negative economic shock.

One such important consequence is for labor market outcomes. Areas which are non-war zones but suffer from sustained terrorist attacks may experience changes in labor market outcomes: firm production can be disrupted through a direct attack of high intensity that destroys and limits its production capacity, workers can perceive the threat of terrorism to be higher at a certain time period and either put in fewer number of hours of work or switch jobs to locations that they perceive as relatively safer. Moreover, as we will explain below, non-war zones are different than war or conflict zones. The effect on labor market outcomes in non-war zones may or may not be similar to the effect on labor market outcomes in war zones.

Notable bombing and explosion incidents have taken place in the first world countries too, such as the Charlie Hebdo attack in France (Henlyey and Willsher 2015), while the unfortunate attack of nine-eleven is still fresh in the memory of many. Developing countries that suffer from similar terrorist attacks, such as Nigeria, Pakistan, Yemen etc., are more vulnerable to terrorism in non-war zones because their relatively weak institutions do not have the capacity to mitigate the negative effects of these attacks or to form efficient policies in post-crisis situation. Thus, understanding the consequences of terrorist attacks in non-war zones is important.

We explore whether these relatively minor but sustained incremental terrorist attacks in non-war zones adversely impact the labor market outcomes and in particular, individual incomes. Second, conditional on this adverse impact, we seek to understand the extent of the effect and the channels that lead to the impact on individual incomes. Furthermore, it is also important to know if terrorist attacks in non-war zones warrant a policy intervention during the crisis or post-crisis. Violence in non-war zones would usually not be expected to receive the same attention from government, policy makers, think tanks, donor agencies etc. However, the extent of the effect on labor market outcomes will determine whether these non-war zones might need assistance in terms of mitigative and preventive policies.

Using an instrumental variable approach, we provide evidence that terrorist attacks in non-war zones decrease monthly earnings. The effect depends on the intensity of the attacks. In other words, it will be incorrect to assume that each attack is of the same intensity. Furthermore, the effect is higher for individuals who experienced at least one terrorist attack in the same month in which they were observed. However, a sizable effect -with important economic significance- tends to persist throughout the year. The most affected group seems to be the service sector workers. The results may be driven by changes in employment compositions across occupations and a decrease in the number of days worked, as a result of the attacks.

These results provide us important insights which are relevant to any region in the world that experiences intermittent bus sustained terrorist attacks in non-war zones. The key conclusion for policy and decision making is that unlike areas which have suffered from persistent conflict, non-war zones do not need aid or intervention that targets all socioeconomic activities. Instead, it will be more efficient to target the aid towards (a) the most vulnerable groups in the labor force [1] and (b) the sectors of the economy directly affected by the violence [2].

It is important to differentiate non-war zones from regions affected by a conventional conflict, war, or civil war. Terrorism -like any other form of violence- involves non-state actors challenging the writ of the government. However, the military or the state is not actively involved in a war against an enemy or a non-state actor (GTD 2017). Second, unlike in a civil conflict, the terrorist or the insurgent group does not directly control some part of the territory. Last, while the attacks are intermittent in nature and they can take place in the form of bombings, explosions, suicide explosions etc., the area is not in a constant situation of a war -a war like situation is more likely to induce migration and wide scale displacement (Grossman et al. 2019), and shut down the economy completely. Instead, normal socioeconomic activities tend to resume after a brief hiatus.

Violence in non-war zones takes the shape of terrorists carrying out sporadic, one-time attacks, on their targets. The targets in this case can include busy urban centers, markets, schools and religious places. These attacks are in the form of bombings, vehicle explosions, suicide attacks, armed assaults etc. and they vary in their intensity. By doing so, terrorist attacks disrupt the usual flow of life and the socio-economic activities. This context is comparable to similar incidences in other countries where certain non-state actors also carry out regular terrorist attacks in non-war zones.

The extent of disruption caused by these attacks is very likely to depend on the intensity and location of the terrorist attacks in an area. For instance, just one small explosion in a sparsely populated area would not be expected to substantially disrupt the socioeconomic activities; the impact of the attack might also not go beyond a radius of a few miles of where the attack took place. On the other hand, a string of intermittent attacks or one big explosion can hinder socioeconomic activities permanently, or at least for a much longer period of time. In other words, disproportionately large

[1] These groups include members of the labor force whose livelihoods are threatened by terrorist attacks, such as those whose place of work is directly affected by an attack.

[2] For instance, attacks in busy town centers will affect service sector disproportionately.

terrorist attacks or sustained minor terrorist attacks can adversely affect the labor market outcomes. Hence,the number of terrorist attacks and the intensity of these attacks play an important role in determining the impact on labor market outcomes.

The country we consider for this analysis is Pakistan. Pakistan has suffered a drastic and sudden rise in terrorist attacks, mostly in the form of explosions and suicide attacks, since the turn of the century -particularly between 2007 and 2014. This drastic rise in terrorist attacks incidents greatly affected Pakistan in terms of both economic and human loss. More than 60,000 Pakistanis have died in terror-related activities since 2002, a third of whom were civilian noncombatants (Neta 2018).

The Khyber Pakhtunkhwa or Khyber PK (KPK) province towards the North-West of the country has suffered the worst because of terrorism (Thompson 2014). There is a marked difference in the number of terrorist attacks in KPK relative to the other provinces [3]. The districts in the KPK province are, hence, the region of interest for the purposes of this paper. The context is discussed in more detail in the Background section. The situation in the KPK province is comparable to other non-war regions in the world that suffer from sustained terrorist attacks such as parts of Northern Nigeria where Boko Haram has regularly carried out terrorist attacks, although Boko Haram also had territorial ambitions (Adelaja and George 2019a).

We use six rounds of repeated cross sectional individual data on labor market outcomes from Pakistan Social and Living Standards Measurement Survey (PSLM) and terrorism data from Global Terrorism Database (GTD). We exploit spatial and temporal variation in the intensity of terrorist attacks and in the individual labor market outcomes in the data to analyze the impact of terrorist attacks on earnings. We employ an instrumental variable technique to isolate the effect of terrorist attacks from unobserved factors that might be correlated with both terrorist attacks and labor market outcomes. We use various robustness checks, explore any heterogeneity in the effects across different segments of the population, and provide a comprehensive discussion on the potential mechanisms driving the results.

[3] Pakistan is divided administratively divided into 4 provinces, namely KPK, Sind, Punjab and Baluchistan.

This paper contributes to the literature on conflict and violence. To the best of my knowledge, there is no study that evaluates the impact of violence in non-war zones on job market outcomes. The context here is different in the sense that there is no official war or conflict going on between two parties in our districts of interest; instead, violence is marked by intermittent bombings, suicide attacks and explosions. Thus, this differentiates the context from current and former active war and civil conflict regions such as, say, Syria, Yemen, Vietnam and Peru. Research shows that afflicted areas countries such as Vietnam, Peru, Indonesia, Nigeria, Guatemala, Peru and Colombia (Miguel and Roland 2011; Duque 2017; Singhal 2018; Dell and Querubin 2017; Dell and Olken 2017; Adelaja and George 2019a; Leon 2012; Chamarbagwala and Morán 2011; Galdo 2013) suffered persistent negative effects of wars and conflicts. [4]

This paper also contributes to the broad body of literature that analyzes the impact of negative economic shocks on adult health, child health, mental health, labor market outcomes, human capital accumulation, household consumption and adult social status (Steckel 1995; Strauss and Thomas 1998; Schultz 2002; Behrman and Rosenzweig 2004; Hoddinott 2006; Almond 2006; Maccini and Yang 2009; Miguel and Roland 2011; Adhvaryu and Nyshadham 2016; Singhal 2018; Currie and Almond 2011; Currie and Vogl 2013). Incremental but intermittent terrorist attacks in non-war zones can be thought of as a negative shock in the form of a “wave of terrorism" that affects a certain geographical area. The impact of this particular type of negative shock is relatively less studied in the literature.

We first provide a context of the area of study in the Background section; followed by a section on Data which discusses the data on the nature of terrorist attacks and the data on labor

[4]Grossman et al. (2019) have looked at the impact of terrorist attacks in Punjab of Pakistan on child health outcomes: using maternal fixed effects, they find that a growing intensity of attacks -defined by fatalities- increases stunting for children experiencing terrorist attacks either during gestation or post-birth in non-war zones. Duque (2017) finds that children exposed to terrorist attacks either pre-birth or post-birth are also at a disadvantage when it comes to human capital accumulation and cognitive development; similar conclusions have been drawn about research on conflict and it's impact on human capital accumulation in Guatemala as well (Chamarbagwala and Morán 2011).

Research has also been conducted on how terrorism affects agriculture and food security (George et al. 2020; Adelaja and George 2019a; Adelaja and George 2019b): increased intensity of Boko Haram attacks in Nigeria reduces agricultural output of various staple crops, the demand for hired labor and the agricultural wages. The effect of these attacks on food security is not severe in the sense that the number of days a household goes without food is not affected but these attacks do limit a household's access to preferred choice of food and the variety of food available.

market outcomes. The section on Conceptual Model provides some comparative statics, based on economic theory, of how a shock in the form of terrorist attacks can affect individual incomes. The Methodology section builds the econometric framework for empirical investigation and provides a causal justification for the interpretation of the results. The next section discusses the main Results followed by a section on Robustness checks, and a section on Heterogeneity Analysis. This is followed by a discussion on the Mechanisms leading to the change in individual incomes, followed by the Conclusion section.

2.2 Background

Pakistan shares a 2,430 kilometer long, largely porous, border with Afghanistan, most of which fell under the jurisdiction of former Federally Administered Tribal Areas (FATA).[5] Following the US led “War against Terror" in Afghanistan that began in 2001, FATA became the hotbed of terrorist camps which fought in Afghanistan (Rashid 2012). Consequently, Pakistani military launched an offensive in 2004 in the FATA region. Militant organizations based in FATA, responded to this offensive by targeting civilian noncombatants all across Pakistan, particularly in Pakistani urban centers (Rashid 2012).

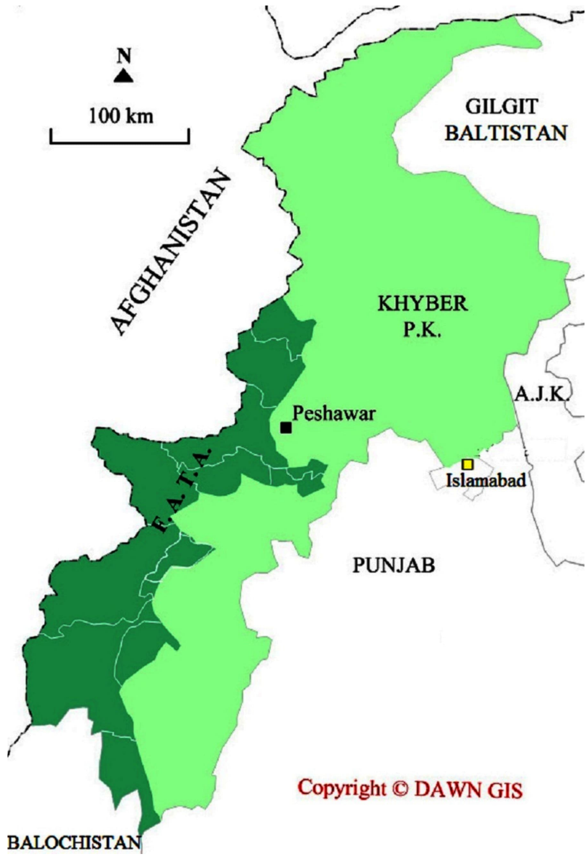
Figure 1 provides a map of FATA, Khyber PK (KPK) and Punjab. The KPK province is in light green color on the map, with Peshawar as its capital which is also the main economic hub of the province. KPK province shares a large boundary with FATA.

It is generally agreed that FATA became the sanctuary for terrorist organizations like Al-Qaeda and the Taliban (Rashid 2012). These organizations had several sub-factions which were involved in terrorist attacks in either Afganistan or Pakistan, or both. The Pakistani military eventually decided to conduct operations against these organizations in FATA, starting from 2003 and subsequent operations were conducted over the following years (Rashid 2012).

Two important sources of data on terrorist attacks are the Global Terrorism Database (GTD)

[5]Until 2018, FATA region was governed directly by the federal government, through appointed political agents; the democratic electoral process has only recently been introduced in these areas for the first time in 2018. In 2018, FATA was merged into the KPK province. As mentioned later in the Data section, our study period is from 2004 to 2014. Hence, the merger does not affect our causal identification and subsequent interpretation of the results.

Figure 2.1 FATA Region, and KPK Province



and Institute of Conflict Management's South Asian Terrorism Database (SATD).[6] Both these data sources show that relative to other provinces, the KPK province suffered the worst due to terrorism. [7] While FATA has been a constant conflict or war zone with a conventional war being fought by the military against the terrorist organizations (Rashid 2012), the KPK province has suffered the most after FATA due to its geographical proximity to FATA.

Between 2000 and 2019, the province has encountered 4,723 suicide attacks and 11,302 explosions (SATD). The rest of the provinces in the country have experienced this form of violence with significantly less intensity. For instance,the Punjab province, which shares its Western border with the KPK province has been affected much less significantly by terrorist attacks where the number of terrorist attacks and the number of explosions in Punjab is 2,473 and 4,456 respectively (SATD),

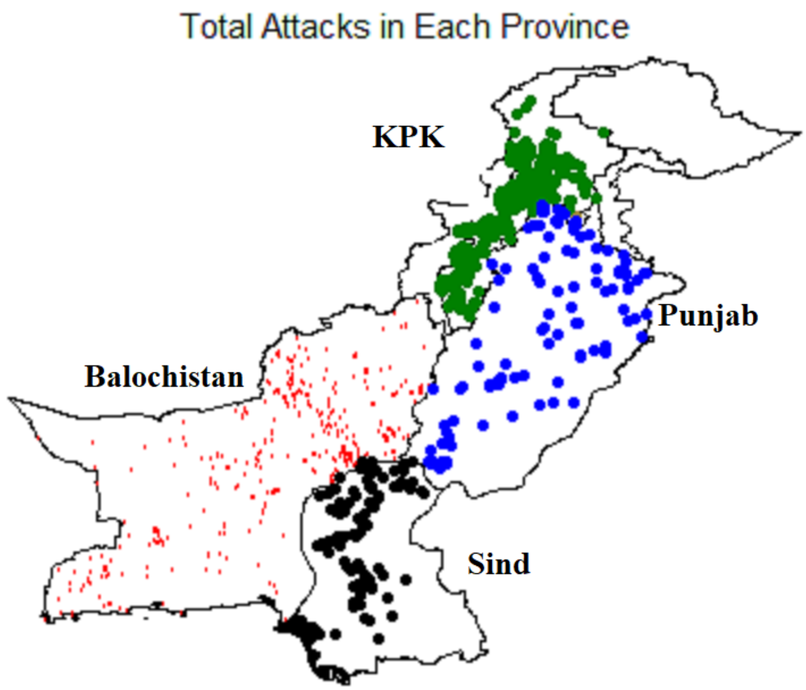
[6] GTD is maintained by National Consortium for the Study of Terrorism and Responses to Terrorism. It is publicly available online through University of Maryland. The Institute of Conflict Management is based in Delhi and maintains a database on terrorism in South Asia.

[7] The data on terrorist attacks is discussed in detail in the next section.

during the same time period. This indicates that the KPK province suffered disproportionately from the war against terror.

Using data from the Global Terrorism Database (GTD), Figure 2 sheds light on the number of terrorist attacks in each of the four provinces of Pakistan. The number of terrorist attacks in each of the 4 major provinces is visible through different colors. Each dot represents one terrorist attack. The difference in intensity can be seen clearly: KPK province has suffered attacks in almost all its districts with a very high frequency [8] Given the number of attacks in KPK, it is clear that KPK shared a disproportionate number of attacks relative to other three provinces.

Figure 2.2 Terrorist Attacks in Each Province, 2004-2014. Source: GTD



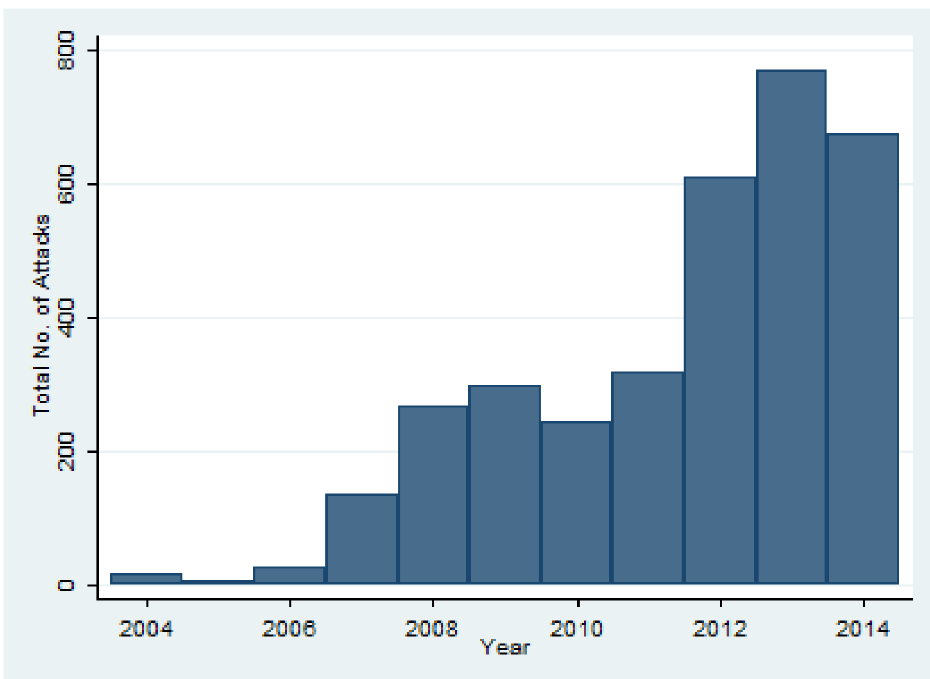
The GTD data records that between 2004 and 2014, 3,163 terrorist attacks took place in KPK, compared to only 326 in Punjab, during the time period 2004-2014. The other two provinces, Sindh and Balochistan, had 1,517 and 2,277 terrorist attacks in this time period, respectively. However, we only consider KPK as the region of interest, because the nature of most attacks in Sindh and Balochistan provinces is different: the majority of terrorist attacks in these provinces

[8] KPK's share of population is 14.69% of Pakistan's population in the 2017 census and 17.58% in the 1997 census. Punjab has the highest share of Pakistan's population at 52.95%, according to the 2017 census. Sindh's share is 23.04% and Balochistan's share is only 5.94%.

were undertaken by political militias seeking some political influence and/or financial goals. In contrast, the attacks in KPK were largely carried out by terrorist groups based in FATA (Rashid 2012); these groups were related to the war in Afghanistan or the “War against Terror" in one way or the other (Rashid 2012). Hence, we only focus on terrorist attacks in the KPK province.

The number of terrorist attacks escalated exponentially in 2007. Figure 3 presents the number of attacks in each year in KPK. The GTD data in fact shows two points at which the number of terrorist attacks in KPK increased during the time-period 2004 to 2014. The number of attacks first increase in 2007 when the wave of terrorism escalated and intensified significantly in 2012, before starting to de-escalate in 2014 [9].

Figure 2.3 Terrorist Attacks in Each Year in KPK Province. Source: GTD



As we will explain in the next section, the terrorist groups’ activities outside FATA mostly targeted civilians. A significant number of bombings and explosions took place in busy urban centers such as marketplaces, town-centers and schools. Thus, these terrorist attacks inflicted deaths and injuries, and disrupted the infrastructure at the site of the attack. By doing so, these attacks disrupted the everyday soioeconomic activities around the site of the attack.

[9]The number of attacks in KPK province in 2015 is not presented in the graph but it decreases to 251 in 2015.

The context described here is comparable to terrorist attacks being carried out anywhere in non-war zones to disrupt the flow of everyday activities; the attacks can be in the form of mass shootings, armed assaults, bombings etc. However, in the context of this paper, these terrorist attacks are not a one time affair: these sporadic and intermittent terrorist attacks carry on for a substantial time duration.

2.3 Data

The first component of the data includes information on individual labor market outcomes and employment details. This information is available from the Pakistan Social and Living Standards Measurement Survey (PSLSM). The cross-sectional PSLM surveys available are for six years: 2004-05, 2006-07, 2008-09, 2010-11, 2012-13 and 2014-15. These surveys are representative at the district level and provide individual level information on individual employment status, income levels, type of occupation and industry, as well as information related to education, health, household size, household assets and infrastructure facilities available in the district.

This information is used to construct our main outcome of interest which is the log of real monthly earnings. The data reports earnings in either the last one month or in the last one year. There are 98,313 individuals across agricultural, manufacturing and services sectors who report earnings. 21,503 individuals report annual earnings [10]. To construct the monthly earnings variable, we divide their earnings by 12 [11]. Among those workers who report annual earnings, about 73% belong to the agricultural sector. This makes sense because it is highly likely that agricultural earnings are more likely to be self-employed and their earnings are also based on the whole cropping season.

The data on terrorist attacks comes from Global Terrorism Database (GTD) which contains geo-coded data of incidents of terrorist attacks around the globe. The data is available from 1970 onwards. The GTD codebook defines a terorist attack as “a threatened or actual use of illegal force

[10] Of these 21,503 individuals, 19,832 work as crop cultivators (either as owners or on contract), share croppers and livestock growers

[11] We also exclude these observations in quite a few specifications. As we will discuss later in the Results section, excluding these observations is a better approach in this context.

and violence by a non-state actor to attain political, economic, religious or social goal through fear, coercion and intimidation." Hence, for any incident to be included in the database it must be intentional, must entail some level of violence or an immediate threat of violence, and the perpetrators of terrorism must be sub-national actors (GTD).[12]

Specifically, GTD considers three criteria for the inclusion of an incident in the database and if at least two of these criteria are met, then the incident is classified as terrorism and is included in the data. These are: (1) the act must be aimed at attaining a political, economic, religious or social goal; (2) there must be evidence of an intention to coerce, intimidate or convey some message to a larger audience; and (3) the action must be outside the context of legitimate warfare activities (GTD). In KPK province, there are 3194 terrorist attacks between 2004 and 2014. The first, second and third criteria are satisfied by 98.69%, 99.72% and 94.86% of the attacks respectively.

Given the above definition and criteria, all attacks carried out by terrorist organizations which were fighting the Pakistani military in FATA -or the US military in Afghanistan- would be classified as terrorist attacks. For the purposes of this paper, we use the number of terrorist attacks between 2004 and 2014 in the KPK province in Pakistan. We also use other information from the data such as the number of fatalities and the number of injuries from these terrorist attacks. Moreover, out of all the attacks recorded in this period, only 5 attacks took place on farms (i.e. less than 0.2% of total attacks), while factories faced no attack during this period.

Next, it is important to discuss the type of terrorist attacks considered here. The data shows that the two most common forms of attacks in KPK between 2004 and 2014 are bombings and armed assaults. About 65% of the attacks were bombings or explosions and about 20% of the attacks were armed assaults. About 8% of the bombings were suicide attacks. Common citizens were the most popular target of these attacks: they faced about 22.5% of the terrorist attacks, followed by police, educational institutes and businesses which faced about 17.2%, 13.9% and 9.4% of the attacks during this period.

Other attacks targeted government officials, military officials, journalists, places of worship,

[12]Specific details about single event incidents, incidents with definition overlap etc. are also provided in the GTD.

telecommunication infrastructure, water supply and utilities infrastructure, transportation networks, airports etc. The share of attacks faced by these entities is much lower, with only government and military officials facing higher than 5% of the total share of attacks.

It is interesting to note that while terrorist attacks did target businesses, there is no mention of a terrorist attack targeting a farm or a factory. GTD defines attacks targeted at businesses as "attacks carried out against corporate offices or employees of firms like mining companies, or oil corporations, chamber of commerce and cooperatives, and hospitals" (GTD). The definition clearly indicates that farms, factories and manufacturing plants are not included in this definition; this anecdotal evidence also suggests that terrorist attacks faced by businesses most likely involved terrorist attacks on the service sector of the economy. Hence, it is most likely the case that farms and factories did not face any direct terrorist attack.

However, this does not imply that farms and factories were not affected by terrorist attacks. Nevertheless, it seems to be the case from the data that some service sector workers did face direct terrorist attacks as terrorists targeted businesses and educational institutes, for instance; but manufacturing and agricultural workers probably did not face any direct terrorist attacks.

The variation across districts in job market outcomes, intensity of attacks and other explanatory variables generates spatial variation in the data, while the temporal variation comes from the changes in these variables over time. As mentioned in the Background section, terrorist attacks escalated in 2007. Therefore, the data for the years 2004 and 2006 can be loosely considered pre-treatment while the remaining four rounds of data can be considered post-treatment.

The summary statistics for individual real monthly income, number of attacks in each district in each year, distance and other time-varying control variables are provided in Table 1. We use log of income as the main dependent variable and the number of terrorist attacks in absolute numbers as the main explanatory variable: it makes interpretation easier in the sense that the percent change in income due to a certain number of terrorist attacks can be analyzed.

Table 2.1 Summary statistics.

Mean and standard deviation of variables.

	(1) N	(2) mean	(3) sd
Individual & Household Variables			
Log Real Monthly Income	101,389	8.561	0.989
No. of Days Worked in a Month	108,462	25.74	5.172
Proportion Employed in Agriculture	119,474	0.323	0.468
Proportion Employed in Manufacturing	119,474	0.198	0.398
Proportion Employed in Services	119,474	0.450	0.498
Household Size	394,519	9.078	4.597
Proportion of Women	394,519	0.506	0.500
Years of Education	363,807	4.363	4.887
Age	394,519	29.64	16.99
District Variables			
Annual District Attacks	138	11.32	30.90
Annual District Fatalities	138	16.67	50.73
Annual District Injuries	138	25.41	78.89
Distance (miles)	23	37.17	33.23
Distance * Predicted Annual Attacks	138	11.24	11,393
District Employment by Active Labor Force	138	93.97	7.054

Notes: The Individual & Household Variables panel includes information from the 6 repeated cross-sections of PSLSM. The District Variables panel mostly includes information from the GTD on terrorist attacks, it also contains information on the instrumental variable and district employment rates.

2.4 Conceptual Model

In this section, we consider a simple conceptual model of how terrorist attacks can affect individual incomes. Terrorist attacks can affect labor market outcomes either directly or indirectly. The direct effect is driven by the loss in production capacity due to attacks. This would be determined by how these attacks affect land, infrastructure and human capital. Frequent terrorist attacks at a location where a firm is based can inhibit the firm's production capacity which will then negatively affect its labor demand. Inputs can be affected in various ways: workers may be injured by a terrorist attack affecting a firm's human capital, or variable inputs like raw material for firms may be destroyed by a terrorist attack of high intensity.

Indirect effects occur through disruptions in the broader socioeconomic environment: a destruction of rail or road network will constrain the availability of raw material to a manufacturing firm, frequent terrorist attacks in urban centers will not only inflict damage on popular recreational spots but also reduce the number of people that visit shopping malls and restaurants, sustained terrorist attacks around a tourist destination -albeit minor in nature- will reduce the number of tourists frequenting the area. All these factors will lead to a reduction in a firm's labor demand.

Consider a firm, i, engaged in production at time period t in any sector of the economy. For simplicity, assume that the individual labor supply is perfectly inelastic. Further assume that each firm produces one good, sold at an exogenous price p. Define the production function of the firm as: $q_{it} = F(l_{it}, m_{it})$ where l_{it} is the amount of labor hired by firm i in year t, and m_{it} is a vector of all other capital and materials that a firm uses including land and variable inputs; with $F'() > 0$ and $F''() < 0$ in both of its arguments. Let w be the cost of labor or the market determined equilibrium wage rate and normalize the price of all other inputs for firm i in year t to 1. Let α_{it} be an exogenous productivity factor specific to a firm's workers that determines worker productivity and depends on worker specific factors such as health, perception of workplace safety, degree of access to transportation for commuting to the workplace etc. Since α_{it} is worker specific, it is not an argument in the production function; it can be thought of as an exogenous factor impacting a firm's production.

Then, under normal conditions, any given firm i's profit function in any given year t is:

$$\pi_{it} = p.\alpha_{it} F(l_{it}, m_{it}) - w.l_{it} - m_{it}. \tag{2.1}$$

Now, consider a terrorism shock S_{it} for firm i in year t, where $S_{it}(f_{it}, z_{it}) \ \varepsilon \ [0, 1]$. The shock depends on the intensity of an attack, z_{it}, and the frequency of the terrorist attacks, f_{it}, such that $S'_{it}(z_{it})$ >0 and $S'_{it}(f_{it})$ >0. Intuitively, the greater the intensity of an attack or the higher the frequency of attacks for a firm, the higher the value of S_{it} on the continuum [0,1].

The production function can be modified to $(1 - S_{it}(z_{it}, f_{it}))F(l_{it}, m_{it})$. If $S_{it}(.) = 1$, the firm is not able to operate anymore and shuts down. This can occur, for example, when an intensity of an attack is very high and destroys the firm's infrastructure completely; or when a very high frequency of attacks makes the area unsafe for operation.

Furthermore, the worker specific factor α_{it} would also be determined by the shock S_{it}. For example, disruption in public transportation infrastructure will make it difficult for a worker to commute to their place of work. Similarly, a worker who is at the sight of a terrorist attack with a high intensity may sustain an injury and will either not show up to work or operate at sub-optimal productivity levels. Different psychological or mental health factors can also play a role. One instance could be where frequent bombings in an area change a worker's perception about the safety of the workplace, thus, affecting their productivity. Hence, it would make sense to assume that $\alpha'_{it}(S_{it}) \leq 0$.

Given the above framework, the firm's profit function in presence of terrorism becomes:

$$\pi_{it} = [1 - S_{it}(f_{it}, z_{it})] \; p.[\alpha_{it} F(l_{it}, m_{it})] - w.l_{it} - m_{it} \tag{2.2}$$

The First Order Condition with respect to labor demand, l_{it} is:

$$\frac{\partial \pi_{it}}{\partial l_{it}} = [1 - S_{it}(f_{it}, z_{it})] \; p.[\alpha_{it} F'_l(l_{it}, m_{it})] - w = 0. \tag{2.3}$$

$$\implies l^*_{it} = l(p, w, S_{it}(z_{it}, f_{it}), \alpha_{it}(S_{it})). \tag{2.4}$$

Equations 3 and 4 above show that a price taking firm's optimal labor demand, in the presence of terrorism is not only a function of prices of output, p, and the labor wage rate, w, but also of the shock $S_{it}(z_{it}, f_{it})$.

If the whole economy is taken into consideration instead of the individual firm, the economy's production capacity contracts due to sustained terrorist attacks in non-war zones since $1 - S_{it}(f_{it}, z_{it}) \leq 1$. This implies that the aggregate labor demand in the economy contracts due to the shock by $S_{it}(f_{it}, z_{it})$. Since we assumed earlier that the labor supply is fixed and hence inelastic to change in the wage rate, an inward shift in labor demand will imply a decrease in the equilibrium wage rate. Below, we obtain this result mathematically through comparative statics.

Equation 3 can be used to obtain an expression for the aggregate labor demand in the economy. Let the aggregate labor supply be $\overline{L}$. Given that labor supply is assumed to be inelastic, the aggregate labor demand should equal the aggregate labor supply in equilibrium. Given that aggregate labor demand is $\overline{L}$, the expression for aggregate labor demand can be obtained by summing the labor demand over all the firms:

$$\overline{L} \; = \; \sum_{i=1}^{N} [1 - S_{it}(f_{it}, z_{it})] \; p.[\alpha_{it} F_l'(l_{it}, m_{it})] \; - \; w \; = \; 0. \tag{2.5}$$

The above equation can be used to obtain an expression for the equilibrium wage rate in the economy:

$$w^* \; = \; \sum_{i=1}^{N} [1 - S_{it}(f_{it}, z_{it})] \; p.[\alpha_{it} F_l'(l_{it}, m_{it})]. \tag{2.6}$$

Equation 6 can be used to do some comparative statistics, and see how the frequency and intensity of terrorist attacks affect incomes. Let $d_t \; \varepsilon \; \{z_t, f_t\}$. Then:

$$\begin{aligned} \frac{\partial w}{\partial d_{it}} \; = -\sum_{i=1}^{N} \; S_{it}'(d_{it}) \; p.[\alpha_{it} F_l'(l_{it}, m_{it})] \; + \\ \sum_{i=1}^{N} \; [1 - S_{it}(f_{it}, z_{it})] \; p.[\alpha_{it}'(S_{it}') F_l'(l_{it}, m_{it})] \end{aligned} \tag{2.7}$$

As defined before $F_l'(l_{it}, m_{it})$ >0 and $S_{it}'(d_{it})$ >0. Thus, the first expression on the right hand side in equation 7, $-\sum_{i=1}^{N} \; S_{it}'(d_{it}) \; p.[\alpha_t F_l'(l_{it}, m_{it})]$ <0. Intuitively, this is equivalent to saying that a contraction in demand for labor decreases the wage rate because the shock negatively affects production capacity of the economy.

Similar results can be shown for the second expression on the right hand side in equation 7. By chain rule, $\frac{\partial \alpha_{it}}{\partial S_{it}} . \frac{\partial S_{it}}{\partial d_{it}}$ <0 because, $\frac{\partial \alpha_{it}}{\partial S_{it}}$ <0 and $\frac{\partial S_{it}}{\partial d_{it}}$ >0. This implies that $p.[\alpha_t'(S_{it}') F_l'(l_{it}, m_{it})]$ <0. Since $[1 - S_{it}(f_{it}, z_{it})]$ ≥0, the second expression in equation 7 on the right hand side $\sum_{i=1}^{N} \; [1 - S_{it}(f_{it}, z_{it})] \; p.[\alpha_{it}'(S_{it}') F_l'(l_{it}, m_{it})]$ ≤0.

The second expression on the right hand side in equation 7 shows how the changes in worker specific productivity levels affect equilibrium wage rate. A decrease in worker specific productivity levels due to the shock will decrease the wage rate. Intuitively, this can happen because of the worker's inability to work when an attack takes place, or any potential health shock suffered due to being a direct victim of the terrorist attack.

In other words, equation 7 has a negative sign as a whole, and hence, the equilibrium wage rate is a negative function of both the intensity of terrorist attacks and the frequency of these attacks.

2.5 Methodology

Our identification strategy exploits variation in the number of terrorist attacks across districts and years. Conditional on the district fixed effects, we examine how changes overtime within these districts are related to labor market outcomes. This approach is able to account for time-invarying unobservable district characteristics such as population density and labor market activity. However, this strategy does not remove time-varying unobserved heterogeneity that may be correlated with both the number of terrorist attacks and labor market outcomes. For example, terrorists may decide to target a district that improves its business climate, and hence, its labor market conditions. Due to this reason, we use an instrumental variable approach.

Consider the following main estimation equation:

$$log(Y_{ijt}) = \beta_0 + \beta_1 Attacks_{jt} + \psi X_{ijt} + \phi_j + \gamma_t + \epsilon_{ijt}, \tag{2.8}$$

where $log(Y_{ijt})$ is the log of real monthly cash income for individual i in district j observed in year t; $Attacks_{jt}$ is the number of terrorist attacks in district j in year t; X_{ij} is a vector of individual, household and district level control variables such as age, gender, education and district level employment rates; ϕ_j is the district fixed effect, γ_t is the year fixed effect and ϵ_{ijt} is the random error component.

We argued in the Background section that the KPK province suffered disproportionately because of its proximity to the FATA region. Hence, the closer a district of KPK province to FATA, the more exposure to terrorist attacks will be expected. Conditional on the distance variable satisfying the exclusion restriction, the shortest possible distance from the center of each district to the FATA boundary can be used as an instrument.[13] The longer the distance, the fewer the predicted number of attacks in that district. However, the distance does not vary overtime and does not allow us to fully exploit the temporal nature of the data.

We follow an approach by Duflo and Pande (2007) to generate temporal variation in the instrument.The identification comes from the fact that the number of attacks in a district in a year depend on (a) the temporal variation in attacks in KPK from the escalation of violence in the year 2007, and (b) the spatial variation in attacks in any year due to the distance from the FATA border. Specifically, we use as an instrument, the predicted number of attacks in a particular year, arising from exogenous factors. Namely, we exploit historical trends of the share of attacks in KPK province and the aggregate increases of violence overtime which are largely determined by the external factors related to confrontation between the government and rebels in the FATA region.

This temporal variation in attacks in KPK can be predicted and interacted with the distance from FATA boundary to construct the final instrument of the following form:

$$Attacks_{jt} = \alpha_1 Distance_j * Predicted\_Attacks_t + \alpha_2 Distance_j + \alpha_3 Predicted\_Attacks_t, \tag{2.9}$$

where $Distance_j$ is the shortest possible distance from the center of district j to the FATA boundary and $Predicted\_Attacks_t$ is the predicted attacks in KPK province for each of the six years for which income data is available. Here, $Predicted\_Attacks_t$ in KPK province is calculated by multiplying the proportion of attacks in KPK in base year in which terrorist attacks escalated with annual attacks in Pakistan in each year. The base year in this case would be 2007. Proportion of terrorist attacks in KPK in 2007 is multiplied with the total annual terrorist attacks in Pakistan. The identifying assumption is that conditional on district fixed effects and other time varying control variables, changes in the number of annual district attacks is based on distance from the FATA border and on the predicted attacks in the KPK province.

[13] As we will show later, there are no trends in individual incomes as a function of distance before 2007.

We also include two interaction terms in this specification. The first term is the interaction of distance with the time dummy; this interaction accounts for time-varying effects of the distance on outcomes of interest. The second term is the interaction between a district level time invarying observable and predicted attacks in KPK in each year $Predicted\_Attacks_t$; this interaction accounts for any differential impact of predicted attacks across districts in a year on outcomes of interest. With this framework, we can also control for district and year fixed effects.

The main estimation equation now would be:

$$\begin{aligned} log(Y_{ijt}) &= \beta_0 + \beta_1 Attacks_{jt} + \psi X_{ijt} + \tau Distance_j * Year_t \\ &+ \kappa M_j * Predicted\_Attacks_t + \phi_j + \gamma_t + \epsilon_{ijt}, \end{aligned} \tag{2.10}$$

where $Distance_j * Year_t$ is the interaction between distance and time dummies; and $M_j * Predicted_Attacks_t$is the interaction between district area -a time invariant observable- and $Predicted\_Attacks_t$. The remaining variables on the right hand side are same as in equation 2.8.

The corresponding first stage equation would be:

$$\begin{aligned} Attacks_{jt} &= \alpha_0 + \alpha_1 Distance_j * Predicted\_Attacks_t + \theta X_{ijt} \\ &+ \omega Distance_j * Year_t + \zeta M_j * Predicted\_Attacks_t \\ &+ \eta_j + \mu_t + \pi_{ijt}. \end{aligned} \tag{2.11}$$

Before we discuss the first stage results, and argue that the instrument satisfies the necessary conditions, a couple of comments are in order [14] . In order to account for the possibility that correlation between individuals living in the same district can result in invalid and downward biased standard errors, we cluster the standard errors at district level. However, the number of districts is just 23. With a low number of clusters, the standard asymptotic tests can over-reject the null hypotheses of no effect (Cameron et al. 2008). Therefore, we bootstrap the standard errors obtained through clustering at the district level by following the wild cluster bootstrap method defined by Cameron et al. (2008).

[14] We also discuss threats to the exogeneity assumption later.

Second, the terrorists carry out sporadic, one-time attacks and target busy urban centers, markets, schools and religious places. Hence, the effect of terrorist attacks will depend on the size of the district: an attack of equal intensity might cause more damage in a more densely populated district than in a sparsely populated district. We account for this by normalizing the annual district attacks by district population.

The first stage regression results from the instrumental variable regression of log of real monthly earnings on annual district attacks are presented in Table 2. Columns 1 and 2 only include the district and time fixed effects. Columns 3 and 4 include other individual, household and district level controls as well. Columns 2 though 4 weight the regression by the annual district fatalities in order to account for the intensity of the attacks. Column 4 includes birth year fixed effects instead of controlling for age as a continuous variable.

The validity of the instrument rests on the relevance and exogeneity conditions. Table 2 establishes the relevance since Columns 2 through 4 show that the first stage F-stat value is above 10 [15] . The results also support our hypothesis that each attack should not be treated as the same and the intensity of the attacks matters. The instrument is strongly and negatively correlated with the number of attacks in a district in a given year. The number of attacks would be expected to increase in the number of predicted attacks in KPK, and they will be expected to decrease in the distance from the FATA boundary. The coefficient can be interpreted as follows: holding the number of predicted attacks in KPK fixed in a year, an increase in distance by one mile reduces the number of attacks by about 0.0012.

The exogeneity of the instrument requires that the instrument only affects the outcome of interest through the endogenous variable. Specifically, the instrument might be correlated with unobserved factors that affect labor market outcomes, leading to a violation of the exclusion restriction. Our instrument has two components, namely distance and predicted attacks, and we will address this concern with regards to both components, respectively.

[15] While the first stage F-stat is just above 10, it is robust to any changes in specifications, as long as the regression is weighted by annual district fatalities. Hence, issues related to weak instrument problem should not be of much concern here.

Table 2.2 First stage results

Dependent Variable: Annual District Attacks				
	(1)	(2)	(3)	(4)
Distance $*$ Prd. Attacks	-0.00047***	-0.00110***	-0.00116***	-0.00115***
	(0.00017)	(0.00034)	(0.00034)	(0.00033)
Kleibergen-Paap F stat	7.618	10.29	11.96	11.91
Observations	98,646	98,646	98,313	81,651
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Weighted by Fatalities	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Year of Birth FE	No	No	No	Yes
Avg. Attacks	15.02	15.02	15.02	15.02
Avg. -Distance * Prd. Attacks	223.1	223.1	223.1	223.1

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

Notes: This table presented results from the first stage estimation of equation 2.11. The dependent variable is the number of annual attacks in each district. The instrument is the interaction of (a) distance to the boundary of FATA region from each district, and (b) annual predicted attacks in KPK province. Column 1 reports first stage results from an IV regression that only includes district and fixed effects as controls. Columns 2-4 weight the regression by the annual fatalities in each district. Columns 3 and 4 include individual, household and district level controls. Column 4 includes birth year fixed effects instead of controlling for age. The standard errors are clustered at district level.

One potential threat with regards to this concern could be differential pre-trends in income as a function of distance from the FATA border. Incomes might be higher (lower) in areas closer (further) to the FATA border even before the violence escalated in 2007. Specifically, incomes should neither be affected by distance, nor trend differently by distance.

To test this, we use the following specification for the two rounds of data from 2004-05 and 2006-07.

$$Y_{ijt} = \delta_0 + \delta_1 Distance_j + \delta_2 2006_t + \delta_3 Distance_j * 2006_t + \lambda X_{ijt} + e_{ijt} \tag{2.12}$$

If districts farther and closer to the FATA boundary do not trend differently in their labor market outcomes before the escalation of the terrorist attacks, we expect δ_3 to be small and statistically insignificant. We present the results in Table 3. Columns 2 and 4 only include observations that reported monthly incomes [16] . In Columns 2 and 4 of Table 3, we exclude the distance variable and include district fixed effects instead. As it can be seen, not only are the coefficients really small but they are also highly insignificant in all the 4 Columns. Hence, it is not likely that there were differential trends in earnings with respect to the distance from the FATA boundary.

Table 2.3 Exogeneity of the instrument: the effect of distance from FATA boundary on earnings.

Dependent Variable: Log Real Monthly Income

	(1)	(2)	(3)	(4)
	Pre-Trends - Year ≤ 2006			
distance	-0.00078		0.00142	
	(0.00186)		(0.00155)	
distance ∗ 2006	-0.00083	0.00037	0.00043	0.00178
	(0.00167)	(0.00186)	(0.00173)	(0.00189)
Observations	25,832	25,832	20,397	20,397
R-squared	0.208	0.217	0.280	0.293
District FE	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Avg. Attacks	0.585	0.585	0.585	0.585
Avg. Log Income	8.008	8.008	8.008	8.008

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

Notes: The results are from the OLS regression of equation 2.12. The dependent variable is the log of real monthly income. The main explanatory variable of interest is the distance from each district to the FATA boundary. Columns 3 and 4 exclude observations that reported annual earnings. Columns 2 and 4 include district fixed effects instead of the time-invarying distance variable. The standard errors are clustered at district level.

The other component of the instrument is the annual number of predicted attacks in the KPK province. Following Duflo and Pande (2007), this is the proportion of total attacks in KPK in 2007 multiplied by the annual total attacks in Pakistan. This can be though of as a Shift-Share Instrumental Variable (SSIV) where the proportion of attacks in KPK in 2007 is the share variable, and the annual attacks in Pakistan is the shock or the shift variable (Borusyak et al. 2021; Goldsmith-Pinkham et al. 2020).

[16]We discuss the motivation behind excluding observations that report annual earnings in the next section

Recent advances in literature identify two different ways in which the exogeneity condition for a SSIV can be satisfied. The first strand of literature focuses on the shock and argues that the instrument is valid if the shock is as good as randomly assigned and the shock incorporates many small independent shocks each with sufficiently small exposure (Borusyak et al. 2021).

Our shock is the total attacks in Pakistan every year. First, it incorporates thousands of individual and small terrorist attacks (each a small independent [17] shock) whose direct effect is local in nature. But, since we exploit within district variation, one concern is that there might be a non-random impact of the shock across districts within KPK province. This is a possibility because the intensity of the shock in a district depends on the distance from the FATA boundary. However, we do control for this by including an interaction term between distance from the FATA boundary and time dummies which accounts for any correlation between the time varying unobservables and the distance from the FATA boundary. We also include district fixed effects in our specifications which control for any correlation with time invariant unobservables. Hence, it can be argued that the shock is random conditional on the set of control variables which also satisfies the orthogonality condition (Borusyak et al. 2021).

The second strand of literature on SSIV focuses on the share component of the instrument. In so far the research design (a) uses a two-share design, or (b) exploits share specific shocks, or (c) exploits differential exogenous exposure to common shocks, then the source of variation is the shares and not the shocks (Goldsmith-Pinkham et al. 2020).

Our share is the proportion of attacks in KPK province in 2007. We have a single share so we do not use a two share design. Second, as discussed in the Background section, the terrorist attacks increased all over Pakistan in 2007, and not just KPK province, so we do not exploit a share specific shock either. However, it is possible that the share of attacks in KPK in 2007 results in differential exposure to the shock. Specifically, the share might be correlated with other unobservables such as demographic changes in a certain year.

Goldsmith-Pinkham et al. (2020) show that strict exogeneity assumption must be satisfied

[17] Each terrorist attack is independent fro the other in the sense that one attack in a certain area in a district does not determine the timing and location of the next attack in that district.

for identification. Specifically, the proportion of attacks in KPK in 2007 should be exogenous conditional on observables. Goldsmith-Pinkham et al. (2020) suggest various specification tests for this purpose. In our context, one relevant specification test will be a placebo test. We will get back to the placebo test shortly.

However, Borusyak et al. (2021) claim that identification is possible with a much weaker assumption. As long as shocks are uncorrelated with the bias of the shares, it does not matter if the shares satisfy the conditional exogeneity assumption. In other words, identification is possible if shares are not associated with the differential changes associated with the shocks.

Our shock is the total attacks in Pakistan every year. Let's assume the shock affects earnings through channels other than annual district attacks in KPK province, and call this bias $\hat{p}_t$. The concern is that $\hat{p}_t$ is correlated with the proportion of attacks in KPK in 2007. For $p_{t\hat{<}2007}$, this correlation cannot practically exist because terrorism wave escalates in 2007, independent of the number of terrorist attacks before 2007. For $p_{t\hat{\geq}2007}$ however, this correlation may exist since the effect of shock on earnings through channels other than attacks may be correlated with the disproportionately high number of attacks in KPK in 2007.

We have addressed this concern in two ways. First, as discussed earlier, we include an interaction term between a time-invariant district characteristic and predicted attacks in our specifications. Conditional on year fixed effects, this interaction term accounts for any unobservable differential impact of the share variable across districts, on outcome of interest, in a particular year.

Second, in our sensitivity analysis later, we include a placebo test as suggested by Goldsmith-Pinkham et al. (2020). Instead of taking distance from the FATA boundary in our instrument, we use distance from the Punjab boundary. The first stage results suggest that the instrument is very weak and the main estimation equation results show no effect on earnings when the placebo instrument is used. We will discuss the placebo test in more detail in the Robustness Checks section, but it would suffice to say here that the placebo test provides evidence that our instrument likely satisfies the much stronger strict exogeneity condition from Goldsmith-Pinkham et al. (2020) that the initial share of attacks in KPK in 2007 are exogenous conditional on observables.

2.6 Results and Discussion

Before presenting the results obtained from the instrumental variables regression, we discuss results from the OLS regression of equation 2.10. The results are presented in Table C1 in the appendix. The standard errors are clustered at district level which are presented in round parentheses while the p-values from the bootstrapped standard errors are presented in the square parentheses. We will follow this convention for other tables presented from here onwards.

The coefficients in both columns of Table C1 in the appendix are very small and not statistically different from zero. Column 2 contains results from the regression weighted by annual district fatalities. The coefficient in Column 1 has a positive sign but the coefficient in Column 2 has the expected negative sign. This adds further strength to our original hypothesis that all terrorist attacks are not the same and the intensity of attacks needs to be considered. The positive sign in Column 1 also suggests that the effect of attacks is correlated with district level unobservables -that also affect income- such as district size, economic activity etc. While district fixed effects account for the time invariant unobservables that might be correlated with the attacks in each district as well as the incomes, the time varying unobserved characteristics of a district can still confound the estimates.

Therefore, in Table 4, we present the main estimation equation results from the instrumental variable approach. Columns 1 and 2 include all the observations, while Column 3 only includes individuals who reported monthly earnings [18]. Columns 2 and 3 weight the regression by annual district fatalities.

All 3 coefficients are negative but only the coefficient in Column 3 is statistically different from zero at 90% significance level. We will not focus on the results in Column 1 because it is not weighted by annual fatalities and both first stage and OLS have suggested that is is important to consider the intensity of the attacks. The annual district fatalities serve as a proxy for the intensity

[18] We restrict the sample, in some specifications, to individuals who report monthly earnings due to two reasons. First, the nature of violence in non-war zones here is in the form of sporadic and intermittent terrorist attacks which is likely to affect monthly income more than annual income. Second, as discussed in the Data section, most of the individuals who report annual income work in the agricultural sector. As also discussed in the Data section, their places of work were not likely to face a direct terrorist attack. Hence, the workers who report annual earnings are probably different from those who report monthly earnings, as far as the effect of terrorist attacks on earnings is concerned.

Table 2.4 The effect of terrorist attacks on earnings.

Dependent Variable: Log Real Monthly Income

	(1)	(2)	(3)
Annual District Attacks	-0.00156	-0.00076	-0.00157*
	(0.00374)	(0.00166)	(0.00082)
Bootstrap P-value	[0.675]	[0.715]	[0.0641]
Observations	98,313	98,313	76,810
R-squared	0.378	0.411	0.458
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Weighted by Fatalities	No	Yes	Yes
Avg. Attacks	16.03	16.03	16.03
Avg. Log Income	8.561	8.561	8.561

Robust standard errors in parentheses

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

Notes: The results are from the IV regression of equation 2.10. The dependent variable is the log of real monthly income. The main explanatory variable of interest is the annual attacks in each district. Columns 2 and 3 present results from regression weighted by annual district fatalities. Column 3 excludes individuals that reported annual earnings. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

of terrorist attacks, albeit an imperfect one -an attack of very high intensity might have taken place in an area where very few people were present. Nonetheless, as discussed previously, these attacks were aimed at areas with a dense presence of people such as schools, places of worship and markets which indicates that the annual district fatalities can serve as a relevant proxy for the intensity of the attacks. Weighing the regression by annual district fatalities means that the attacks in any district in any given year are not treated as of equal intensity anymore.

As discussed before, the terrorist attacks considered here are local in nature. Terrorist attacks impact a limited area in a non-war zone: the economic activities outside of a radius of a few miles might not be affected. Unlike other negative shocks such as a flood or a drought which are more likely to disrupt the socioeconomic activities of the whole district, the impact of a terrorist attack is likely to be very localized. This would be particularly true for attacks with low intensity. Hence, it is most likely the case that individual incomes are negatively affected only when the attacks are intensive enough to substantially disrupt the socioeconomic activities of an area.

This perhaps helps explain why we only see an effect only for individuals who report monthly incomes. The effect of these terrorist attacks is likely to be more prominent for individuals with unstable incomes such as daily wage earners. Unfortunately, we do not have information on whether an individual is a daily wage earner, so we canot verify this.

Another important factor that should be considered is the frequency of the attacks. Because of the intermittent nature of these attacks, the frequency of attacks probably has an important role to play. About 50% of the individuals observed in the data are in districts which experience between 1 and 15 terrorist attacks in a year; for individuals in districts with 15 annual attacks, this implies an average of 24 days between each attack. However, about 20% of the individuals observed in the data are in districts which experience between 15 and 60 terrorist attacks in a year; for individuals in districts with, say 60 annual attacks, this implies an average of 6 days between each attack. More frequent or sustained attacks even minor in nature, are much more likely to cause a greater disruption in a district's economic activities.

As far as the size of coefficient in Column 3 of Table 4 is concerned, it implies that one additional attack reduces monthly earnings by about 0.16 percent, on average. Given the average number of attacks, this suggests a 2.5 percent reduction in earnings overall. If we consider the standard deviation, a one standard deviation increase in terrorist attacks reduces earnings by 6.5 percent. However, the standard deviation of attacks is very high at 41.3, so we will stick to the more conservative average number of attacks for understanding the interpreting the magnitude of the effect of terrorist attacks.

Furthermore, following the conceptual model, terrorist attacks can also affect worker specific productivity factors. This effect can manifest itself in different ways. For instance, a salaried employee may not be able to commute to work if transportation network is not functioning or a daily wage laborer may not be able to work for a few days if they sustain an injury, thus reducing their number of days worked.[19]

Indirect effects, such as higher stress levels can also reduce worker productivity, negatively affecting their income. Unfortunately, empirical evidence cannot be provided because of the data's inability to connect each worker's workplace and household location to each attack, and because of lack of data for some health and psychological outcomes.

Next, we consider the timing of the attacks relative to the time when an individual was observed in our data. Specifically, we identify the month in which an individual was observed. This allows us to focus on those individuals who, say, experienced a terrorist attack in their district in the same month in which they were observed. We use this information to see if consecutively experiencing a terrorist attack in the past few months leads to a differential impact on earnings.

The results are reported in Table 5. Panel A includes all the observations while Panel B only includes individuals who reported monthly earnings. In both panels A and B, Column 1 only includes individuals who experienced an attack in their district in the same month in which they were observed. Column 2 narrows the sample to individuals who experienced a terrorist attack in their district in the month prior to being observed as well. Column 3 similarly narrows the sample further to individuals who also experienced an attack in the two months prior to being observed in our data.

As with the main results in Table 4, the results are more robust when individuals who report annual incomes are excluded. In Panel A, only the coefficient in Column 2 is statistically different from zero at 90% significance level but the significance does not hold if we consider the p-value obtained from the bootstrapped standard errors. In Panel B, all the columns have a statistically significant coefficient at 99% significance level.

In both panels, the coefficient size increases when we consider individuals who experienced an attack in their district in two consecutive months but it decreases when we only consider individuals who experienced an attack in three consecutive months. However, the drop in the coefficient in Panel B is very small and not meaningful in terms of the magnitude of the impact on earnings.

[19]We will discuss this in greater detail in the mechanisms section.

Compared to Table 4, the qualitative interpretation of the results is the same. However, the size of the coefficients in Panel B of Table 5 is more than twice the size of the coefficients in Column 3 of Table 4. In Column 1 of Panel B of Table 5, an additional attack reduces earnings by about 0.33 percent on average, for individuals who report a monthly income. If we consider the overall average number of attacks, this translates to an average reduction in earnings by about 5.3 percent. However, if we just consider the individuals who experienced a terrorist attack in the same month in which they were observed, their average for annual district attacks is much higher at about 44, which translates to a decrease in earnings by about 14.7 percent. This is a significant reduction in earnings.

The coefficient in Panel B of Table 5, however, does not change much when sample is restricted, in Columns 2 and 3, to individuals who have consistently experienced violence. This might suggest that a substantial chunk of the effect of terrorist attacks in non-war zones on earnings is short-lived. Specifically, this effect does not seem to extend beyond one month. It must be noted, however, that in Table 4 we identified that there is a reduction in earnings by 2.5 percent which is high enough to be a matter of concern for the policymakers.

Coming back to our findings in Table 5, one way to test a part of the effect in Table 5 is indeed short-lived is to explore the effect on individuals who have not experienced a terrorist attack in their district during the month when they were observed. We report the results in Table C2 in the appendix. The coefficient is extremely small and it is not statistically different from zero. If we consider the overall average number of attacks, this translates to an average reduction in earnings by about 0.32 percent for these individuals.

This lends strength to the evidence that a major chunk of the effect of terrorist attacks on incomes is short-lived and most likely does not extend beyond a month. However, there is still an economically significant effect on earnings which persists, as identified in Table 4. This finding makes sense given the nature of the attacks. Immediately after an attack, individuals probably experience a very high decrease in their earnings. However, unlike a conflict or a civil war, the economy does not shut down completely. The effect is limited to a few miles within the radius of the attack. Furthermore, since normalcy is restored to the area a few days after the attack [20], the level of socioeconomic activity probably also returns back to normal levels. However, as the findings of Table 4 suggest, not all loss in earnings is restored overtime. We investigate this in more detail later in the Mechanisms section.

Table 2.5 The effect of terrorist attacks on earnings (by timing of attacks).

Dependent Variable: Log Real Monthly Income			
	(1)	(2)	(3)
Panel A: All Observations			
Annual District Attacks	-0.00283	-0.00374*	-0.00247
	(0.00197)	(0.00226)	(0.00200)
Bootstrap P-value	[0.374]	[0.349]	[0.397]
Observations	62,919	56,992	53,271
R-squared	0.423	0.435	0.440
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes
Panel B: Observations Reporting Monthly Incomes			
Annual District Attacks	-0.00332***	-0.00388***	-0.00323***
	(0.00095)	(0.00110)	(0.00119)
Bootstrap P-value	[0.00601]	[0.0100]	[0.0100]
Observations	42,159	36,448	32,808
R-squared	0.465	0.475	0.483
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes
Avg. Attacks	44.13	58.59	76.64

Notes: The results are from the IV regression of equation 2.10. The dependent variable is lof og real monthly income. Column 1 includes individuals whose district faced at lease one attack in the month they were observed. Columns 2 and 3 only include individuals who additionally experienced an attack in the previous one month and previous two months respectively. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

[20] This implies that businesses, schools and religious places open again at full capacity.

Our main finding, hence, is that there is a reduction in incomes due to relatively minor but sustained terrorist attacks in non-war zones. However, there is a catch to it. A major chunk of the effect goes away because the area's production capacity does not take a permanent hit. In other words, the production possibility frontier does not move inwards, like it is typically expected to do when a war or conflict takes place. Nonetheless, there is still an economically significant reduction in incomes that persists throughout the contemporaneous year which warrants attention from policymakers.

The general direction of these findings is consistent with the the literature on terrorism in non-war zones. The fact that the intensity of attacks plays an important role in determining the effect on labor market outcomes is supported by the previous studies[21] (Adelaja and George 2019a; George et al. 2020; Grossman et al. 2019). Additionally, we also find that there is a very high impact of terrorist attacks on earnings as the immediate aftermath of violence. However, some chunk of it goes away as the socioeconomic activities of the area return to normal levels. we It is however more difficult to compare the results of this study to research on long term consequences of conflict, for instance, in Vietnam and Peru (Miguel and Roland 2011; Galdo 2013). This study looks at the contemporaneous effect of terrorist attacks and does not say anything about the long term consequences of violence in non-war zones.

2.7 Robustness Checks

In this section, we address two plausible threats to identification and check the sensitivity of our estimates. We consider two important threats to identification in the subsection below, following it with sensitivity analysis.

Since the outcome variables are conditional on being employed and hence being an active member of the labor force, individuals might be able to self-select themselves in and out of the labor market. If the selection is non-random, it can result in biased estimates. For instance, the

[21] The previous findings that agricultural wages are negatively affected by terrorist attacks in Nigeria (Adelaja and George 2019a) and the fact that this effect depends on the intensity of the terrorist attacks are also corroborated by this paper's findings.

terrorist attacks might make it more difficult for the relatively less skilled labor force to find jobs or to go to their place of work, eventually forcing them to opt out of the labor force. In that case, the estimates for individual incomes in the previous section would be biased upwards in terms of the absolute size of the coefficient.

To test this hypothesis, we employ a linear probability model where the dependent variable equals 1 if an individual is working. The right hand side of the equation is same as in equation 2.10. The results are presented in Table 6. The results show that terrorist attacks have no impact on employment, on average: as shown in Table 6, the coefficient in both the regressions is not only non-negative but more importantly, it is also statistically insignificant. Additionally, the coefficient in both the columns is extremely small. This suggests that the effect of terrorist attacks on the average probability of being employed is virtually zero. The results in Table 6, thus, show that a potential confounding factor is not an issue which lends credence to the claim that the estimates identified in the previous section are indeed causal.

Another potential threat to identification is out-migration, although migration and permanent displacement are more likely to take place in war-zones. Literature also suggests that violence in non-war zones typically does not lead to permanent displacement (Grossman et al. 2019). However, if a district experiences a very high frequency of attacks, or a few attacks of very high intensity, it may induce people to move to safer districts. If this migration is non-random it can bias our estimates. For instance, if the migration patterns are driven by highly educated workers, then the incomes for those individuals would not be observed and the estimated coefficient would be biased downwards. In general, the direction of the bias will be unknown unless the migration pattern can be disaggregated by skill levels.

While we do not have data on migration history in the PSLSM, we test for this by following the approach used by Maccini and Yang (2009). We regress the annual sample size in each year-district-birth year group, on the annual number of terrorist attacks in each district. The right hand side is the same as in equation 2.10. The results are presented in Table 7.

Column 1 of Table 7 includes the district-year-birth year groups for all individuals in the sample

Table 2.6 The effect of terrorist attacks on labor market participation.

Dependent Variable: =1 if Employed		
	(1)	(2)
Annual District Attacks	0.00043	0.00014
	(0.00087)	(0.00065)
Bootstrap P-value	[0.683]	[0.845]
Observations	392,261	392,261
R-squared	0.278	0.339
District FE	Yes	Yes
Time FE	Yes	Yes
Weighted by Fatalities	No	Yes
Avg. Attacks	15.02	15.02
Proportion Employed	0.292	0.292

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

Notes: The results are from the IV regression of equation 2.10. The dependent variable is a dummy variable that equals 1 if an individual is employed. The main explanatory variable of interest is the annual attacks in each district. Columns 2 weights the regression by annual district fatalities. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

who are of working age. The coefficient is not statistically different from zero in Column 1. However, we are more concerned about the migration patterns of individuals who are employed since the results in Table 6 suggest that there is no effect on employment. Therefore, Column 2 of Table 7 narrows the sample down to the district-year-birth year groups of individuals who are employed. However, since the results in previous section suggest a more robust effect on individuals who report monthly earnings, Column 3 further restricts the sample by excluding the district-year-birth year groups of individuals who report annual earnings.

The coefficients in all 3 Columns of Table 7 are not statistically different from zero. Furthermore, the coefficient in all 3 columns has a positive sign which suggests that out-migration or permanent displacement is not a concern in this case. Nonetheless, the size of the coefficient is not small by

Table 2.7 The effect of attacks on observed sample size.

Dependent Variable: Log of Annual District Sample Size by Year of Birth			
	(1)	(2)	(3)
Annual District Attacks	0.01137	0.01136	0.01134
	(0.01000)	(0.01067)	(0.01061)
Bootstrap P-value	[0.390]	[0.450]	[0.448]
Observations	14,777	11,514	11,484
R-squared	0.666	0.549	0.550
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes
Avg. Attacks	9.400	9.345	9.328
Avg. Sample Size	27.99	33.39	33.46

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

Notes: The results are from the IV regression of equation 2.10. The dependent variable is the log of district sample size in each year. The main explanatory variable of interest is the annual attacks in each district. Column 1 includes year-district-birth year groups of all individuals who are of working age. Column 2 narrows down the sample to year-district-birth year groups of individuals who are employed. Column 3 further restricts the sample by excluding individuals who report annual earnings. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

any means which is a cause of concern. Therefore, as a robustness, check, we re-run the estimation specifications in Table 4 and Table 5 that were presented in the Results section.

The results are presented in Tables C3 and C4 in the appendix. The specifications in Table C3 in the appendix are comparable to the specifications in Table 4 in the previous section. Similarly, the specifications in Panels A and B of Table C4 in the appendix are comparable to those presented in Table 5 above. For all the results presented in Tables C3 and C4 in the appendix, the size of the coefficient estimates does not change much and the efficiency of the estimates improves slightly. Hence, any potential out-migration is not only ruled out but it is also shown that any changes in sample size is not a potential confounder for the estimates identified in the Results section.

Another concern could be that the impact of terrorist attacks differs by the size of the district. In the specifications presented above, we normalized the annual district attacks by district population.

Now, we normalize the annual number of attacks in each district by district area instead of district population. We present the results in Table 8.

Table 2.8 Weighting the attacks by district area (as a robustness check).

Dependent Variable: Log Real Monthly Income

	(1)	(2)	(3)	(4)
Annual District Attacks	-0.00039*	-0.00081***	-0.00097***	-0.00081***
	(0.00023)	(0.00028)	(0.00032)	(0.00030)
Bootstrap P-value	[0.0891]	[0.0130]	[0.0200]	[0.0140]
Observations	76,690	42,159	36,448	32,808
R-squared	0.458	0.466	0.476	0.484
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes	Yes
Avg. Attacks	15.04	21.47	55.01	72.53
Avg. Log Income	8.562	8.562	8.562	8.562

Robust standard errors in parentheses

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

Notes: The results are from the IV regression of equation 2.10. The dependent variable is log of real monthly income. The main explanatory variable of interest is the annual attacks in each district, normalized by district area here instead of district population. In all the 4 Columns, individuals who reported annual earnings are excluded. Column 2 includes individuals whose district faced at lease one attack in the month they were observed. Columns 3 and 4 restrict the sample further to individuals whose district experienced an attack in the previous one month and previous two months respectively, in addition to the current month. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

The results can be interpreted as the effect of an additional attack per 1,000 square kilometers. Only those individuals who reported monthly earnings are included in all the 4 specifications. Column 2 only includes individuals who experienced an attack in their district in the same month in which they were observed. Column 3 narrows the sample to individuals who experienced a terrorist attack in their district in the month prior to being observed as well. Column 4 restricts the sample further to individuals who also experienced an attack in the two months prior to being observed in our data.

The size of the coefficients in Table 8 is substantially smaller compared to the results presented and discussed earlier. However, the efficiency of the estimates remains the same. The qualitative interpretation of the results does not change much but the size of the estimates suggests that the effect on earnings is substantially higher when there is an increase in the number of attacks relative to district population, compared to when there is an increase in the attacks relative to district area.

Last, we also conduct a placebo test to establish the validity of our instrument. The KPK province is bordered by the FATA region on the Western side and the Punjab province on the Eastern side. We know that terrorists come in from the FATA area and the proximity of a district in KPK province to the FATA boundary is an important determinant of the attacks. The same is not true about the proximity of a district in KPK province to the Punjab boundary, since there is no or very little infiltration of terrorists from the Eastern side. This placebo test establishes that distance from FATA boundary is indeed an important determinant of terrorist attacks in a district, and that there is no terrorist infiltration -and hence terrorist attacks- coming from a different location or region bordering the KPK province.

Therefore, one placebo check could be to use the shortest possible distance from the center of each district to the Punjab boundary in the instrument, instead of the distance from the center of each district to the FATA boundary. We use the modified instrument and report the main estimation equation results in Table 9.

Column 1 of Table 9 includes all observations while Column 2 excludes individuals who reported annual earnings. In both the Columns, the coefficient has a positive sign suggesting that there is no negative effect on income of attacks when this modified instrument is considered. Furthermore, both the coefficients are not statistically different from zero. The absolute size of the coefficients in Table 9 is also small and not of any economic significance. Moreover, the first stage F-statistic for both the regressions is less than 1 suggesting that the modified instrument is a very weak instrument [22].

[22]The first stage results for this modified instrument are not presented in the paper. They are available with the authors.

Table 2.9 A placebo test: using distance from Punjab boundary in the instrument.

Dependent Variable: Log Real Monthly Income		
	(1)	(2)
Annual District Attacks	0.00882	0.00018
Bootstrap P-value	[0.253]	[0.972]
	(0.00947)	(0.00677)
Observations	98,313	76,810
R-squared	0.404	0.458
District FE	Yes	Yes
Time FE	Yes	Yes
Weighted by Fatalities	Yes	Yes
Avg. Attacks	16.03	16.03
Avg. Log Income	8.561	8.561

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

Notes: The results are from the IV regression of equation 2.10, but with a modified instrument to serve as a placebo check. The dependent variable is the log of real monthly income. The main explanatory variable of interest is the annual attacks in each district. The instrument is modified to measure distance from the center of each district from the Punjab boundary. Column 2 excludes individuals that reported annual earnings. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

2.8 Mechanisms

It has been shown so far that terrorist attacks do affect incomes of the labor force and this effect depends on the intensity and the frequency of the attacks. Understanding the channels through which the effects of violence occur in non-war zones is important for determining the role of policy makers. In this section, we discuss the potential mechanisms that drive this impact on individual incomes.

Two potential pathways through which terrorist attacks can potentially affect incomes are demand side and supply side factors in the labor market. We can link this back to the section on

Conceptual Modeling of this problem, where the reduction in earnings can be driven either by (a) loss in production capacity of the firm and disruption in the broader socioeconomic framework of the area, and (b) an effect on the worker specific productivity factor, which we defined as α_{it} in the conceptual framework. While data limitations prevent us from providing data on the former, we provide some evidence on the latter in this section.

We have information available on employment compositions across different occupations and on the number of days worked in a month. Changes in employment compositions due to terrorist attacks, will suggest that workers switch jobs as a consequence of terrorist attacks. This can affect worker productivity, thus decreasing marginal product of labor at each level of hiring, which can translate into a reduction in income.

Similarly, a reduction in the number of days worked per month can also affect worker productivity. For instance, a terrorist attack may cause labor to feel unsafe while traveling to work or an attack on a transportation network may inhibit workers from traveling to their place of work [23]. However, a reduction in number of days worked may also be caused by a direct attack on the place of work since it reduces the production capacity. In all cases, nevertheless, we can expect a decrease in earnings.

We first explore changes in employment compositions as a potential channel linking the effect of terrorist attacks on incomes. Table 10 presents results from instrumental variable regressions where dependent variable equals 1 if an individual is employed in a certain occupation. The results can be interpreted as the change in probability of being employed in a certain occupation classification, due to an additional terrorist attack. These occupations are categorized in the data as follows: senior officials, professionals, clerks, sales, skilled agriculture, crafts and trade, plant operations, and elementary occupations. A detailed breakdown of occupational classifications, as provided with the PSLSM data, is provided in Appendix D.

From Table 10, we can identify how terrorist attacks induce labor force members to switch jobs across 8 different occupational classifications. The first two categories, in Columns 1 and 2, identify

[23]We do know from the GTD database, however, that the attacks on transportation and communication networks are very small in number

Table 2.10 Changes in occupational compositions as a potential mechanism.

	Employment Composition							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Senior Official	Professionals	Clerks	Sales	Skilled Agriculture	Craft & Trades	Plant Operator	Elementary Occupation
Annual District Attacks	0.00123***	-0.00143***	-0.00026*	0.00114	-0.00057	-0.00016	-0.00013	0.00020
	(0.00024)	(0.00050)	(0.00013)	(0.00131)	(0.00108)	(0.00045)	(0.00035)	(0.00051)
Bootstrap P-value	[0.0120]	[0.0310]	[0.0751]	[0.472]	[0.752]	[0.769]	[0.745]	[0.651]
Observations	118,611	118,611	118,611	118,611	118,611	118,611	118,611	118,611
R-squared	0.090	0.229	0.052	0.103	0.246	0.067	0.035	0.076
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proportion of Workers	0.034	0.0827	0.0207	0.247	0.308	0.0640	0.0636	0.180
Avg. Attacks	38.88	20.92	25.62	12.75	7.665	29.86	21.33	15.21

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

Notes: The results are from the IV regression of equation 2.10. The dependent variable in each Column is a dummy variable that equals 1 if an individual works in the respective occupation. The main explanatory variable of interest is the annual attacks in each district. Individuals who reported working as unpaid house helpers, or those, who reported employed but haven't gone to work in the last 28 days are also included. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

changes in employment composition of senior officials and professions, respectively. As defined in Appendix D, these two classifications comprise of skilled labor force members, who are highly likely to possess a college degree. We can see in Table 10 that there is an increase in the workers classified as senior officials and a decrease in workers classified as professionals, due to terrorist attacks. This perhaps seems to suggest that skilled workers switch from jobs such as teachers, health professionals, librarians and police inspectors to jobs such as managers, government officials and legislators [24].

This switch can be explained by looking at the data on terrorist attacks. It was noticed that police, educational institutes and businesses were one of the most frequently targeted entities which faced about 17.2%, 13.9% and 9.4% of the attacks, respectively, during this period. Educational institutes and police premises typically employ service sector labor force. GTD defines businesses as "attacks carried out against corporate offices or employees of firms like mining companies, or oil corporations, chamber of commerce and cooperatives, and hospitals". This definition suggests that businesses mostly consist of service sector jobs under GTD's definition.

Overall, about 40% of the attacks were faced by police, educational institutes, and businesses which employ service sector workers, with a high likelihood that most of their workforce is highly skilled. This perhaps explains why we see most jobs being switched by Professionals, Clerks and Senior Officials.

Hence, it is possible that skilled members of the workforce considered jobs such as government officials, armed personnel etc much safer than working as teachers and police inspectors which places them in more dangerous situations where threat to their lives and property is significantly higher. Linking this back to the worker specific productivity factor in the Conceptual Model section, a switch in the nature of occupation due to terrorist attacks affects productivity negatively which likely translated into a reduction in monthly earnings.

We see very small changes in the proportion of labor employed as skilled agricultural workers,

[24]Switching jobs that require a high degree of specialization or skill is not always possible. For instance, a health professional cannot become a legislator and vice versa. However, switching some managerial and administrative jobs is a possibility. A marketing specialist may take up an administrative job in the government sector, for instance.

and plant and machinery operators. Farms, and factories and manufacturing plants most likely did not face any direct terrorist attacks. This is because farms are a part of rural setting in any developing country and factories are usually located away from busy urban centers. As discussed before, most attacks targeted schools, police stations, businesses and civilians in busy town centers. Since we are looking at the contemporaneous effect on incomes, it is likely that any learning on the new occupation is still taking place and the productivity levels have not caught up yet. Thus, this may lead to a decrease in contemporaneous monthly earnings.

Results from Table 10 also suggest that some workers had to adjust to a new occupation. Most of the workers who switched jobs originally belonged to the service sector. These workers probably lacked experience, training and qualifications required for their new jobs. Hence, their productivity in new jobs is very likely to be lower in their new occupations. In a perfectly competitive labor market, this would imply lower wages for these workers in their new jobs compared to their previous jobs. This can be a potential channel that helps explain the decrease in earnings due to terrorist attacks in non-war zones.

The second potential pathway that can affect incomes is the reduction in the number of days worked. Information is available on the number of days worked in a month for each worker. In Table 11, we present the results with the log of number of days worked in a month as the outcome of interest. Column 1 includes all observations. The remaining Columns include observations for each of the 8 occupations. The results measure the percentage change in number of days worked per month due to an additional terrorist attack, on average.

The results in Table 11 suggest that labor force members in some service sector occupations see a reduction in the number of days worked due to terrorist attacks, but the most prominent reduction is for those in skilled agriculture, and in crafts and trades. Given the average number of attacks, there is a 2.5 percent reduction in the number of days worked by skilled agricultural workers due to terrorist attacks. While the coefficient size is the largest for this occupation, skilled agricultural workers experience much less terrorist attacks in a year. The overall average for annual district attacks is 16.03 while it is only 7.66 for skilled agricultural workers. The opposite is true

Table 2.11 Changes in number of days worked as a potential mechanism.

Dependent Variable: Log No. of Days Worked in a Month									
	(1) All	(2) Senior Official	(3) Profess- -ional	(4) Clerks	(5) Sales	(6) Skilled Agriculture	(7) Craft & Trades	(8) Plant Operator	(9) Elementary Occupation
Annual District Attacks	-0.00038	-0.00152**	0.00022	-0.00039	0.00049	-0.00316**	-0.00227*	0.00020	0.00137
	(0.00050)	(0.00077)	(0.00055)	(0.00072)	(0.00061)	(0.00136)	(0.00123)	(0.00075)	(0.00104)
Bootstrap P-value	[0.514]	[0.116]	[0.753]	[0.645]	[0.601]	[0.0450]	[0.163]	[0.796]	[0.221]
Observations	107,441	3,995	9,531	2,455	26,968	29,071	7,276	7,383	20,837
R-squared	0.078	0.069	0.084	0.030	0.078	0.092	0.100	0.052	0.117
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. No. of Days Worked	25.74	27.50	27.99	28.32	26.62	24.84	24.83	27.34	24.01
Avg. Attacks	15.02	38.88	20.92	25.62	12.75	7.665	29.86	21.33	15.21

Robust standard errors in parentheses

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

Notes: The results are from the IV regression of equation 2.10. The dependent variable is the log of number of days worked per month. The main explanatory variable of interest is annual attacks in each district. Column 1 includes all observations. The remaining Columns restrict the sample to the respective occupation. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

crafts and trades workers who experience about 30 attacks on average. Given the average number of attacks, these workers experience a 6.8 percent reduction in their number of days worked per month. Senior officials also see a 5.93 percent reduction in their number of days worked per month, given the average number of attacks -they face almost 39 attacks on average which is the highest in the sample.

The coefficient size of estimates in Table 11 also entail some discussion. Given the average number of days worked per month, it only translates to a reduction of about 1 to 1.5 days in the number of days worked per month in almost all cases. These estimates can be compared with the coefficient estimates in Table 10 to get a sense of the extent of the effect through each pathway. The coefficient estimates in Table 10 are more varied across Columns, than the coefficient estimates in Table 11. In Column 2 of Table 10, the coefficient estimate translates into a decrease in the probability of working as a Professional by about 3 percent, given the average number of attacks. This change is much smaller for those working as Clerks, whose coefficient estimate translates into a decrease in likelihood of working as a Clerk by about 0.7 percent.

Another possible mechanism is that terrorist attacks result in injuries to the labor force members which affects their productivity at work. It will be partially accounted for in the reduction in the number of days worked per month. However, if there is an increase in the probability of being sick or injured, it also helps explain this channel. We have information available in our data on individuals who were sick or injured in the last 14 days. We use this information to construct a dummy variable that equals 1 if an employed individual was sick or injured in the last 14 days [25]. Next, we see if terrorist attacks increase the probability of being sick or injured in the past 14 days.

The results are presented in Table C5 in the appendix. Column 1 includes all employed individuals while Column 2 only includes those who reported annual earnings. Column 3 restricts the dataset to individuals who experienced a terrorist attack in the same month when they were observed. All the coefficients except in Column 3 have the expected positive sign. However, the size of this coefficient is very small and it does not have any economic significance. None of the

[25]Unfortunately, we cannot separate out the sick and the injured.

coefficients is statistically different from zero.

This makes sense because the terrorist attacks were intermittent and sporadic in nature. The average number of annual attacks is 16 which implies an attack every 22 days, on average. This is unlike a war or a conflict where there can be multiple attacks in a single day. Additionally, we could not find a newspaper report suggesting that the local health care systems were overwhelmed by one or more terrorist attacks. Hence, we can rule out this potential mechanism that can drive the impact of terrorist attacks on earnings in non-war zones.

Overall, it may be the case that terrorist attacks have a more severe impact on service sector workers since they are more likely to be directly exposed to terrorist attacks. Service sector jobs are more likely to be based in urban centers and markets where most of the attacks took place. Members of the workforce based in the service sector can not only experience a shock to their specific productivity factors -as they are more likely to be present in areas where attacks take place- but their places of work are also more likely to be attacked directly. The two potential channels driving this impact are changes in employment compositions across occupations and reduction in the number of days worked per month. Changes in firm demand could also impact earnings but lack of firm data does not allow us to explore it as a potential mechanism.

2.9 Conclusion

In this paper, we examined how violence in non-war zones can affect labor market outcomes. In the context of terrorist attacks in the KPK province of Pakistan, we find that the effect of violence in non-war zones on individual incomes depends on the intensity of violence. It does not exist for individuals who report annual earnings, such as farmers who earn at the end of the season. Our results point to the high likelihood that a substantial chunk of the effect exists only in the same month in which labor force members experience an attack in their district. Nonetheless, in terms of economic significance, there is a sizable reduction in earnings that persists throughout the contemporaneous year. The most likely pathways leading to the negative affect on individual incomes are the changes in employment compositions and reduction in number of days worked in a month.

Violence in non-war zones is local in its impact relative to violence in war or conflict zones. This is because the terrorist attacks are intermittent and sporadic in nature. Therefore, (a) violence mostly affects socioeconomic activity levels within the radius of a few miles around the attack and (b) the socioeconomic activities tend to resume a few days after an attack.

Our research provides some important insights for understanding the impact of violence in non-war zones on incomes. These findings are relevant to any region of the world where intermittent but sustained violence takes place in non-war zones. The mechanisms presented here highlight the importance of working in a secure, peaceful and stable environment. Unfortunately, in a context where a disproportionately large proportion of terrorist attacks target civilians, it is difficult to ensure a secure and peaceful work environment.

However, the government and policy makers can play a role in violence non-war zones to mitigate the effects on labor market outcomes. The key conclusion for policy and decision making is that unlike areas which have suffered from persistent conflict, non-war zones do not need aid or intervention that targets all socioeconomic activities [26]. Instead, it will be more efficient to target the aid towards the more vulnerable groups of the society. Any policies such as cash transfer programs or relief efforts can be targeted towards them which will increase the efficiency of policies.

Policy makers can also identify the locations that have suffered a loss in their production capacity due to sustained violence in non-war zones. For instance, if a very large number of terrorist attacks are aimed at destroying the communication infrastructure, policy makers would need to prioritize their relief efforts towards workers in industries whose supply chain network is most likely to be affected. Similarly, relief efforts can be targeted towards businesses, educational institutes and police stations because they face a disproportionately high number of attacks.

In addition, it seems to be the case that service sector workers have to adjust the most due to terrorist attacks. This is most likely because of their greater exposure to terrorist attacks. The security of their workplaces seems to be threatened the most due to these attacks. Thus, ensuring

[26]For instance, Europe received aid under Marshall Aid Plan after the second World War which was aimed at developing and rebuilding all sectors of the European economies.

the safety of the workplaces for those whose livelihoods are directly affected might play a critical role in mitigating the magnitude of the effect of terrorist attacks on earnings.

The government can also take some preventive measures to reduce the intensity of the attacks. Since the intensity of attacks play an important role in determining the impact of terrorist attacks, mitigating the intensity of these attacks can help reduce the magnitude of the effect on incomes. The preventive measures can include deployment of security personnel and placement of security check points at relevant locations. These measures might help by preventing the terrorists from carrying out an attack at the location of their intended target. Smartly designed preventive measures will also help enhance the safety of work places for those workers whose workplaces are more likely to be exposed to terrorist attacks.

With regards to preventive security measures, it must be noted that most developing countries and their law enforcement institutions do not possess enough capacity to implement effective mitigating measures. Investment in capacity building of law enforcement institutions in violent non-war zones can, hence, prove pivotal in mitigation strategies. This implies that at least some proportion of the aid, if provided as part of relief efforts, can be targeted at capacity building of law enforcement institutions with a special focus on preventing terrorist attacks in non-war zones.

Last, we want to point out the limitations of this piece of research. We only look at the contemporaneous affects of violence in non-war zones on earnings. We do not evaluate the impact of this kind of violence on earnings in the medium or long run which can be the subject of a future piece of research. In order to improve our understanding of individual labor market decisions, there is also a need to analyze the impact of terrorist attacks on the changes in the attitudes, aspirations and resilience of the labor force due to terrorist attacks.

CHAPTER 3

MASS INVOLUNTARY MIGRATION AND EDUCATIONAL ATTAINMENT

3.1 Introduction

Historical events are known to shape economic development (Acemoglu et al. 2011; Bannerjee and Iyer 2005; Chaney and Hornbeck 2015; Dell 2010; Dippel 2014; Nunn 2008). One such event is forced migration. There is substantial literature in development economics on migration, with the canonical foundations established by Harris and Todaro (1970), and Todaro (1986). This strain of literature mainly focused on rural urban migration. More recent literature tries to understand the selection of migrants across borders (McKenzie et al. 2010), ability to migrate from rural areas in developing countries (Jayachandran 2006), and the link between remittances sent by migrants and household investments (Yang 2008). There is also a plethora of literature on migrant networks (Munshi 2003; Munshi and Rosenzweig 2016; Swee 2017).

Forced migration has not only been an important issue historically but also in the contemporary world. The United Nations High Commissioner for Refugees reports that at least 65 million people are currently displaced globally due to wars, conflicts and natural disasters. Historically, forced migrations have taken place because of wars such as the Second World War which caused mass migration of Poles, terrorism such as the sustained bombings in civil areas of Pakistan's formerly FATA regions which resulted in about 1 million internally displaced people and conflicts such as the conflict in Afghanistan since Cold War which resulted in migration of Afghan refugees to other countries.

In addition, migrants have been known to have increased demand for education which suggests that forced migration in early stages of life might not affect outcomes such as education in the same adverse way other negative shocks have been known to do. Asmoz Oz wrote in his autobiographical novel that "it was always like that with Jewish families: they believed that education was an investment for the future, the only thing once can never take away from your children, even if, Heaven forbid, there's another war ... another migration." (Oz 2005). The idea that forced migration increases the demand for education has been put forward in economic theory (Brenner and Kiefer 1981), but its empirical evidence had proven to be elusive until recently (Becker et al. 2020; Botticini and Eckstein 2012). Forced migrants typically differ from locals along socioeconomic and cultural characteristics such as skill set, work ethics, language, ethnicity and religion (Becker et al. 2020), thus affecting their educational choices differently, relative to the native population.

On the other hand, experiences in early life are known to shape later economic outcomes in life such as human capital development (Almond and Currie 2011; Currie and Vogl 2013). Negative shocks in early life such as wars and extreme weather are known to negatively affect individual performance on economic outcomes such as education and wages (Singhal 2018; Maccini and Yang 2010; Galdo 2013; Leon 2012). Forced migration or permanent displacement in early stages of life is an interesting economic theme to study because migration presents challenges as well as opportunities. However, forced migration is a shock whose effects have proven particularly difficult to estimate (Becker et al. 2020; Botticini and Eckstein 2012) because of the many confounding factors involved.

In this paper, I explore a unique historical setting to study the effect of forced migration on the human capital investment for migrants who were of school going age when they were forced to migrate. I use the partition of Pakistan and India in 1947 as the event of interest which led to mass scale migration on both sides of the border between 1947 and 1951. This migration was based on religious lines and led to mass scale violence on both sides of the border.

Using Pakistan's National Census of 1973, I identify individuals whose country of birth is India and individuals whose country of birth is Pakistan. I classify Individuals born in India and living in Pakistan, by 1973, as migrants. I subsequently identify individuals from birth cohorts who were of the school going age in 1947 and individuals who were older than the average school going age in 1947. Following Duflo (2001), I use a differences-in-differences type analysis to estimate how the event of partition affected the educational outcomes of migrants of school going age relative to the natives in the same birth cohorts.

Using the educational outcomes of individuals who were older than the average school going age, I show that in the absence of the event of partition in 1947, educational outcomes were only determined by the sum of a time trend and a time invariant migrant status fixed effect. Specifically, I first provide evidence that migrant individuals who were older than the average school going age in 1947 did not differ in their educational outcomes from native individuals of same birth cohorts, thus satisfying the parallel trends assumption required for a differences-in-differences type analysis. I also address several other concerns related to identification such as the differential rate of immigration across different districts, systematic differences across birth cohorts, selective migration of more (or less) educated migrated families, and the potential determination of the border by educational outcomes as a possible source confounding the estimates.

Additionally, I pay close attention to the recent literature on the issues of bias and power (Rambachan and Roth 2022; Roth 2019; Freyaldenhoven et al. 2019), heterogeneous treatment effects (Chaisemartin and D'Haultfoeuille 2022), dynamic effects in treatment studies (Sun and Abraham 2020), and variation in treatment timing (Goodman-Bacon 2021). The context studied in this paper does not lead to dynamic effects or variation in treatment timing. However, the issues of confounding estimates, bias and power are very relevant. I discuss their implications for the results presented in this paper, and present some empirical evidence to alleviate these concerns.

I find that migrants of school going age were more likely to achieve certain educational goals and this is particularly true for younger cohorts. These migrants are more likely to complete 5, 10 and 12 years of education respectively -all three milestones are important in the Pakistani educational system and achieving any one of them significantly alters opportunities available in the job market.

Pakistan and India split in 1947 on the eve of the departure of the British. The partition was ostensibly along religious lines. The partition offers a unique opportunity to explore the consequences of permanent involuntary migration (Bharadawaj et al. 2008). An estimated 14.5 million people migrated in the 4 years after migration, while another 2.2 million did migrate but went missing and were most likely killed in the violence that ensued (Bharadwaj et al. 2008).

There were significant demographic shifts in both India and Pakistan as a consequence. Bharadwaj et al. (2008a) show that the out-migrating Hindus and Sikhs from Pakistan were more literate than the resident Muslim population in Pakistan. Similarly, the in-migrating Muslims into Pakistan from India were also more literate than the resident Muslims in Pakistan. The district of Karachi in Pakistan had 28% of its population classified as migrants [1]. In 1951 and the 91% of the literate population of the Karachi district were migrants (Bharadawaj et al. 2008).

Bharadwaj et al. (2008) also point out that migrants engaged in non-agricultural professions were more likely to settle into larger cities and to migrate to larger distances. Migrants who were more literate were also more likely to settle into larger cities and to migrate to larger distances. Furthermore, existing literature around the event of partition found that those migrants who went to India are more productive than the resident population in India (Bharadwaj and Fenske 2011) and the districts which received these migrants have higher agricultural yields in India (Bharadwaj and Mirza 2019).

Research from other parts of the world on permanent displacement and education shows that individuals from Poland had no differences in educational attainment before the Second World War but descendants of Poles who migrated are more educated 80 years after the war than other Poles (Becker et al. 2020). A study on educational outcomes of about 15,000 Ethiopian Jewish kids who involuntarily airlifted to Israel found that early schooling environment has important consequences for high school dropout rates, repetition rates and the passing rate on matriculation necessary to enter college (Gould et al. 2004).

The literature also suggests that the educational environment faced by young migrant children is critical in shaping their future outcomes (Gould et al. 2004). Heckman (2000) argues that early investment in human capital has a larger return than investments at a later stage aimed at closing the gap between regular and troubled students. Duflo (2001), Krueger and Whitmore (2001), Currie (2001), and Garces et al. (2002) substantiate this claim with empirical evidence.

However, the consequences for educational attainment are not well understood when the migrants are not necessarily immigrating to opportunity. In the context considered in this paper, the

[1] Karachi is a major metropolitan city of Pakistan and it is also the most densely populated. Majority of literate migrants chose to settle in big cities like Karachi (Bharadawaj et al. 2015).

receiving country is a developing country that has just gained independence as a state after large scale violence along religious lines. In addition, the simultaneous exodus of the colonial British government had left a governance and administrative vacuum. Hence the context is different from the context considered by Gould et al. (2004) in several ways.

First, the country considered here is a developing country; this implies a low literacy rate, lack of awareness about importance of education and limited access to educational infrastructure; besides, enrollment was not mandatory in Pakistan at that time. Second, the country had just faced mass scale violence along religious lines which suggests that the more important priorities of the government would be related to maintenance of law and order, and not ensuring enrollment of migrant children. Third, the colonial era British government had just left and the country had just been carved out on the map suggesting that there is a constitutional, administrative and legislative vacuum severely inhibiting the government's capacity to plan and execute any policies including educational policies. Last, the migration was at a much larger scale where about 14.5 million people were permanently displaced which means that, as far as policies related to the welfare of the migrants are concerned, the government's immediate focus was on settling the migrants and providing them with shelter.

Hence, this paper adds to the literature on the consequences of forced migration by studying the impact on educational outcomes of a large-scale forced migration into a nascent, war-torn country. The consequences of forced migration for migrants of school going age are not well understood when migrants are not necessarily immigrating to opportunity.

This research also contributes to the extensive literature that links historical events to subsequent economic development by studying outcomes such as income, health and human capital. However, while I believe these results to be an important contribution to this literature, it is equally important to point the limitations of this paper. First, I specifically, and only, examine the educational outcomes of migrants of school going age relative to the natives from the same birth cohorts. I do not compare the educational outcomes of migrants to individuals who did not migrate. Second, I do not study the subsequent economic outcomes of these migrants such as income and wealth.

This is partly due to the paucity of data on other outcomes of interest.

Last, I must point out a limitation of this paper that, as discussed, partition was a two-way phenomenon which resulted in demographic changes, mass violence and deaths, end of colonial era, new governments, the birth of a new country and increased religious homogeneity. Hence, interpreting the results solely as a consequence of partition alone will be a mistake.

The following section provides a brief Background of the event of partition in 1947. This is followed by a section on Data where I explain the construction of birth year groups and discuss other characteristics of the data. Next, there is a section on Empirical Methodology which outlines the relevance of the differences-in-differences-approach and provides evidence against the potential pitfalls that can confound the identification. This is followed by the Results section where I present my main results. The next section is on Robustness which explores the robustness of results to different cut offs for school going age, addresses concerns related to bias and power limitations, and discusses results from alternative identification methods discussed in the recent literature. The last two sections, respectively, discuss the potential Mechanisms that can help explain the channels driving the results and provide a Conclusion that summarizes what this paper does.

3.2 Background

The possibility of the partition of British India after the departure of the British Raj had been on the cards for a few years before the event of partition took place in 1940. The official campaign for a separate state had been officially initiated by the Muslim League in March 1940. However, when the official partition and departure of British hastily took place in 1947 -instead of June 1948 as planned earlier- it was sudden, horrific, violent and chaotic for millions who found themselves on the wrong side of the India-Pakistan border that had just been carved out (Bharadwaj and Mirza 2019). An estimated 14.5 million people were displaced as a result of the partition (Bharadwaj et al. 2008).

The official plan of partition was laid out by the British in a plan called the 3^{rd} June Plan. It brought forward the departure of British and the proposed creation of two new states of India and

Pakistan from June 1948 to August 1947. It also laid the foundations for redrawing the boundaries between India and Pakistan which vaguely stated that boundaries would be demarcated by the contiguous majority areas of Muslims and non-Muslims. A British civil servant Cyril Radcliff was tasked with the responsibility of drawing the borders who lacked any knowledge of the area or of the people (Yong and Kudaisya 2000).

Two related policy decisions further aggravated the situation. First, Radcliff used the 1941 census to calculate religious demographics at district level but the 1941 census was believed to be heavily rigged by certain religious groups because Muslim League had initiated its official campaign for a separate Muslim homeland a year ago (Bharadwaj and Mirza 2019). The resulting demarcation cut off communities from their sacred places of worship, disregarded railway lines and forests, and separated industrial plants from their agricultural supply lines (Khan 2017).

Second, Radcliff made a decision to to keep the demarcation decisions secret until the very last minute (Bharadwaj and Mirza 2019). This decision speaks to the lack of Radcliff's knowledge about the religious and cultural sensitivities of the area. Consequently, many Muslims and Hindus found themselves on the wrong side of the border on the eve of the Partition when two new countries were formed. Once the partition line was revealed, mass scale violence began on both sides of the border with numerous incidents of rioting between Muslims on one side and Hindus and Sikhs on the other (Bharadwaj and Mirza 2019).

This context provides important insights that will be very relevant for identification purposes later. Since the official decision to split Indian subcontinent into two states was announced in June 1947 and the partition took place in August 1947, it is not very likely that any anticipatory behavior was there among migrants. This claim is also supported by the literature on partition (Yong and Kudaisya 2000; Bharadwaj et al. 2008; 2015). Furthermore, the process of drawing the boundary line by Cyril Radcliff took many by surprise and they found themselves on the wrong side of the border overnight. Hence, it is very less likely that migrants were able to migrate before 1947 in anticipation of the announcement of the 3^{rd} June Plan.

Next, Jha and Wilkinson (2012) established that violence was a major determinant of migratory outflows. Their research shows that districts with a higher presence of demobilised soldiers from the Second World War experienced greater levels of violence in 1947. The higher levels of partition-related violence in turn led to greater outflow of evacuees in such districts. Hence, individuals in districts with more violence were more likely to migrate. Moreover, violence was based purely along religious lines which rules out selection of permanently displaced migrants based on wealth, skills and other socio-economic characteristics.

I will now briefly discuss the immediate consequences of partition. Bharadwaj et al. (2008) find a replacement effect whereby districts that experienced large scale outflows also experienced greater inflows of migrants. This replacement effect was present for both countries. Additionally, more educated Hindus and Sikhs moved out of Pakistan while more educated Muslims moved into Pakistan. Consequently, the net effect on characteristics such as literacy was not of any economic significance in both India and Pakistan (Bharadwaj et al. 2015).

Second, migratory inflows were greater in the major urban centers of both India and Pakistan (Bharadwaj et al. 2008). Bharadwaj et al. (2008) term this a big city effect; they also find that more educated migrants were more likely to travel greater distances in search of better economic opportunities that were on the offer in the major urban centers.

Last, the resettlement of refugees increased literacy and caused a shift towards the non-agricultural professions (Bharadwaj and Mirza 2019), because the migrants were overwhelmingly concentrated in non-agricultural professions such as trade and commerce, and because farmers were unable to acquire land either of the same size or of the same quality compared to what they had left behind (Bharadwaj et al. 2015). The last two consequences are of major importance and can help understand potential pathways that drive the results found in this paper.

3.3 Data

I use the Housing, Economic, Demographic Characteristics (HED) Survey of 1973 for Pakistan, available through IPUMS. The HED survey was implemented in the second phase of the 1972 census [2]. The survey was administered to about 300,00 households and the sample includes about 2% of Pakistan's population.

The weighted survey data contains information on country of birth, birth year, household size, family size, years of living in the same district and educational outcomes. The information on educational outcomes is categorical and not continuous. The country of birth can be used to identify those individuals who migrated from India to Pakistan [3].

I only include individuals living in Punjab and Sindh provinces of Pakistan. These provinces share a border with India and hence, almost all the migrants settled in these two provinces. This is reflected in the data as well. These two provinces hosted about 98.9% of the total migrants from India in 1973. The other two provinces are Baluchistan and Kyber-Pakhtunkhwa (KPK); they only had 1.2% and 0.5% of their population classified as migrants from India in the survey data. Baluchistan, for instance, had less than 28,000 migrants as per the 1951 census (Bharadwaj et al. 2015).

The main outcome of interest is an indicator variable that equals 1 if an individual has completed 10 years of education. Secondary education in Pakistan is completed at 10 years of education and it is considered an important milestone in an individual's education. It also enables one to seek various clerical jobs in private or government sectors. Additionally, I use two other outcomes of interest which are indicator variables for completing 5 and 12 years of education, respectively. Completing 5 years of education is equivalent to completing primary education in Pakistan, and ensuring universal primary education is an important Sustainable Development Goal. Meanwhile, completing 12 years of education makes one eligible for applying to college and seeking higher education and skilled expertise.

I assume that most individuals would have competed 10 years of education by the age of 16. In most countries -including Pakistan- the average age of starting formal schooling is 5 to 7 years.

[2] The first phase consisted of a full count census.

[3] Although, it is possible that some individuals migrated before the partition happened, but as discussed in the Background section, it is very likely. The bulk of migration took place between 1947 and 1951. First, Bharadwaj et al. (2008) point out that the demographic changes I discussed in the Introduction section only happened between 1947 and 1951.

This implies that anyone born after 1931 would be less than 16 years of age, and hence, would be considered of school going age -later in the Robustness Analysis section, I change the average age of completion of education to 18 years.

The sample consists of 354,239 native individuals and about 117,948 migrant individuals who were born between 1923 and 1953. Since the sample consists of only 904 migrants after 1951 (which makes sense since almost all the migrants had migrated by 1951), there are not enough migrants born after 1951 in the sample relative to natives born after 1951, I drop the observations for the years after 1951. This leaves 308,546 native individuals and 117,044 migrant individuals in the sample. Table 1 presents the number of natives and migrants in each group while Table 2 presents the summary statistics for different individual, household and district characteristics for both groups.

Table 3.1 Sample size for migrants and natives in 7 groups. Each group consists of 4-5 birth cohorts.

Number of migrants & natives in each group

	Natives	Migrants
$Birth_{1947-51}$	91772	7901
$Birth_{1942-46}$	58820	26823
$Birth_{1937-41}$	50536	25249
$Birth_{1932-36}$	42194	21908
$Birth_{1927-31}$	34187	18935
$Birth_{1923-26}$	31037	16228
N	354239	117948

The number of individuals born in India drops drastically for individuals born after 1951. Hence, the youngest cohort included is the one born in 1951, 4 years after the partition took place. Furthermore, the sample size is too small for the individuals aged above 50 because the life expectancy was only about 54 years in 1973 (World Bank 1973). In other words, the sample size is too small for individuals born before 1923.

The year of the event is defined as 1947, since that was the year British colonial government departed and the partition formally took place. Hence, the sample includes individuals between 24 years of age in 1947 up until individuals born 4 years after 1947. In terms of year of birth, this corresponds to the oldest birth cohort from 1923 and the youngest birth cohort from 1951. This implies that the individuals born from 1923 to 1931 can be considered as those who were older than the school going age of 16 years in 1947.

The subsequent identification, which I will discuss in the next section, relies on a differences-in-differences type approach. The temporal variation is generated by birth cohorts born in different years from 1923 to 1951. The spatial variation is generated by their migration status; individuals can be either migrants born in India or natives born in Pakistan. The interaction term between these two variables is the explanatory variable of interest.

In addition, an inspection of data revealed that for older age cohorts, most of the observations are clustered around multiples of 5. For instance, there are many more observations for individuals aged 50 than for individuals aged 46-49. This could be because of a recall problem since most individuals from about a century ago didn't keep proper birth records in many developing countries. It is also well-known that formal records were not stringently maintained in the Indo-Pak subcontinent at that time. To deal with this issue, I group birth cohorts into six bins of 4-5 year intervals: 1923-26, 1927-31, 1932-36, 1937-41, 1942-46 and 1947-51.

Additionally, I use data on literacy rates and religious composition of the population from three different censuses. These include the 1931 Census of India, the 1951 Census of India and the 1951 Census of Pakistan. The 1931 census of India was conducted by the British government. Hence, this census data comes from before the partition of India into two states and the drawing of the border line in 1947. Hence, similar information is available for all districts regardless of whether they are in India or Pakistan. The 1951 Census data was collected separately by the governments

Table 3.2 Sample characteristics of Migrants and Natives.

Summary statistics for migrants and natives

	Natives	Migrants
Family size	5.911	6.340
	(3.452)	(3.411)
Hh size	5.987	6.366
	(3.463)	(3.424)
No. of families in a Hh	1.054	1.036
	(0.418)	(0.293)
No of own children	2.029	2.917
	(2.096)	(2.403)
Male children ever born	1.817	2.444
	(1.597)	(1.787)
Female children ever born	2.096	2.778
	(1.693)	(1.869)
Percentage living in a different district 8 years ago	0.0681	0.0600
	(0.252)	(0.238)
District's population eligible to be in labor force	34146.1	53049.0
	(24343.2)	(27694.7)
District's active labor force	15822.4	24586.4
	(11150.9)	(12674.8)
N	308546	117044

The mean values for migrants and natives are provided in this table.
The standard deviation for each variable is provided in parenthesis

of India and Pakistan and there are some differences in the information collected by both countries respectively. Pakistan, for instance, does not report the district of origin for the migrants and India, for instance, does not report literacy and other information separately for migrants.

I use this data to provide descriptive statistics that help understand the extent of the migration. In particular, the changes in religious composition in some districts between 1931 and 1951 can help us understand better (a) the magnitude of the migration or permanent displacement, and (b) the evidence that migration was motivated by violence along religious lines alone and not by skill, literacy, wealth or other socioeconomic characteristics.

3.4 Empirical Methodology

The empirical methodology here is informed by the context described in the Background. The partition of Indian subcontinent into two states, the departure of British, and the ensuing violence and civil war in 1947 is a significant event in the history of the subcontinent. Hence, an event study approach is perhaps very relevant for studying an outcome of interest.

Additionally, there is information available on the country of birth which allows me to construct bins of control groups for each bin of treatment group. In other words, for each birth cohort of migrants in a bin, there exists a birth cohort of natives.

Next, my outcome of interest tracks the completion of an educational milestone. To the best of my knowledge, the British government did not implement any differential policies for migrants and natives before 1947. Any shocks or changes in policies before 1947 -such as the recruitment of soldiers for the Second World War- were very likely to have equally affected both migrants and natives, as defined for the purposes of this paper. I am also not aware of any specific policies implemented in the region that formed Pakistan before 1947 which would result in the educational outcomes of natives trending differently.

Hence, it makes sense to hypothesize that, after accounting for the trend, there will be no or very little differences in educational outcomes of migrants and natives who had completed their 10 years of education before 1947. This hypothesis informs the empirical approach described below.

Before I describe the empirical approach, I must also mention how the theory on migration in the development microeconomics literature is relevant here. The classical literature mostly looks at rural-urban migration (Harris and Todaro 1970; Todaro 1986), migration networks(Munshi 2003; Munshi and Rosenzweig 2016; Swee 2017), and selection of migrants when it comes to international migration (McKenzie et al. 2010). Unlike the context in this paper, almost all of these works look at the individual migrant's or family's decision to migrate. Yet, they help a researcher in hypothesizing about the pathways that might determine the consequences of permanent displacement. Specifically, the location and occupation decisions taken by migrants may be very crucial channels that drive the treatment effect we identify in the next section.

The empirical methodology relies on a differences-in-differences type estimation approach. The empirical estimation equation in a differences-in-differences type analysis needs to demonstrate that the parallel trends assumption holds or that the differences in the treatment and control group before the event are stable. In other words, after accounting for the time trend, the difference between the treatment and control groups before the event takes place should not be statistically different from zero. Additionally, the size of the coefficient should be sufficiently small.

Second, as discussed in the Introduction, the event of forced migration was intertwined with significant political, social, economic and cultural changes. This suggests that, for estimates to be causal, the estimation strategy should control for the characteristics of migrants from India, natives in Pakistan and non-migrants in India who did not migrate. This would ensure that the estimates comparing the migrants with the natives are causal, conditional on a set of control variables which can be correlated with the event of partition and/or consequences of migration.

However, it is next to impossible to define “non-migrants in India who did not migrate": these individuals would be likely to be classified as Muslims but it is further impossible to classify Muslims who did not migrate despite their fellow Muslims migrating from India to Pakistan. I will, however, argue later in this section that although those individuals facing a higher threat to their lives and property were more likely to migrate, the violence was not likely to be disproportionately aimed towards more (or less) educated individuals.

Nevertheless, I can control for individual and household characteristics, birth cohort characteristics, and the differential characteristics of the migrants and natives in Pakistan. As I will discuss below, my estimation strategy effectively controls for all of these characteristics of the migrants and the natives.

The empirical specification can be written as:

$$\begin{aligned} Y_{ihj} = {} & \beta_1^g birthyear_{ihj}^g + \beta_2^g (birthyear_{ihj}^g * migrate_{ihj}) + \alpha_1 X_{ihj} + \alpha_2 Z_{hj} \\ & + \eta_j + \epsilon_{ihj}. \end{aligned} \tag{3.1}$$

Here, Y_{ihj} is the outcome of interest for individual born in year i in household h in district j, and $birthyear_{ihj}^g$ refers to the g^{th} bin to which an individual born in year i belongs, where $g \in [1, 6]$, but β_1^1 is not estimated due to multicollinearity. Individuals are classified into six bins according to their year of birth. These bins classify individuals into the following six birth year groups: 1923-26, 1927-31, 1932-36, 1937-41, 1942-46 and 1947-51.

Similarly, $migrate_{ijh}$ is an indicator variable that equals 1 if an individual was born in India and migrated to Pakistan, X_{ihj} and Z_{hj} are vectors of individual and household level controls respectively and η_j are district fixed effects. The controls include sex and age of an individual [4], household size, family size, number of children in the household, number of families in the household, a dummy that equals 1 if an individual lives in the urban area of the district, and a dummy that equals 1 if an individual lived in a different district 8 years ago. The main coefficients of interest are β_2^g where $g \in [1, 6]$.

What is this coefficient estimating? The main outcome of interest is an indicator variable which equals to 1 if an individual has completed 10 years of education. For each birth cohort group, or for each of the six bins $g \in [1, 6]$, β_2^g estimates the difference in the probability of completion of 10 years of education for migrants, relative to that of natives. For instance, β_3^2 estimates this probability for migrants born during the period 1927-31, relative to the natives born in the same period.

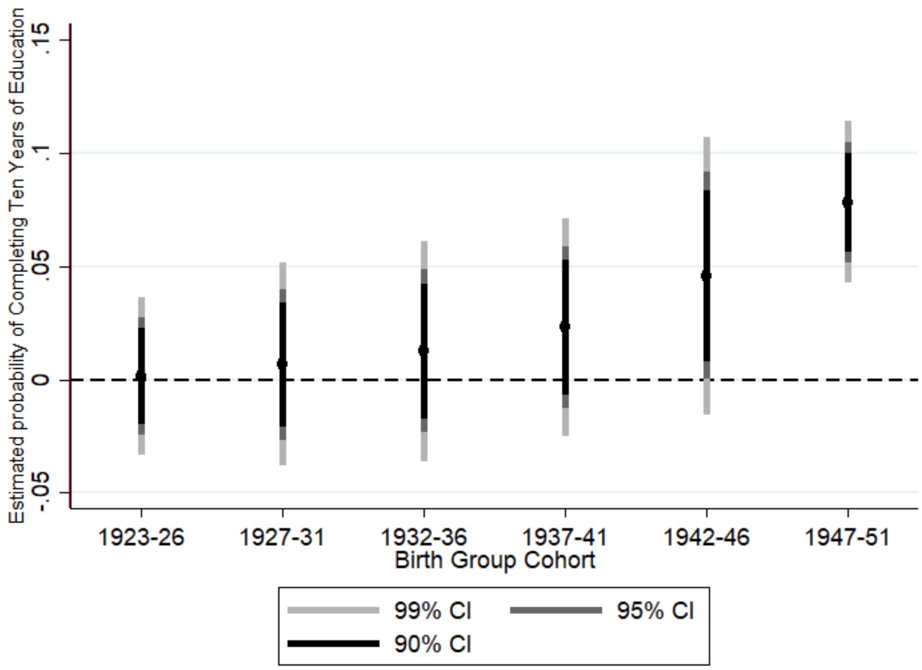
Figure 1 plots the coefficients β_3^g from the estimation of the above equation, along with their confidence intervals. As far as the pre-trends assumption is concerned, the difference between migrants and natives who are aged above 16 should be zero. Hence, the two coefficients of interest for this purpose are for migrants who belong to the 1923-26 birth year cohort and the 1927-31 birth year cohort.

As it can be seen in Figure 1, the probability to complete 10 years of education is the same as that of the natives for migrants belonging to the 1923-26 and 1927-31 birth year cohorts. The coefficients are not statistically different from zero, and more importantly, the size of the coefficient is extremely small and not of any practical significance. It shows that the parallel trends assumption holds for the cohorts who were older than 16 -and hence, above the school going age- in 1947.

[4] In some specifications, I will use birth year fixed effects instead of birth year group fixed effects

In other words, after accounting for the trend in the birth year cohorts, the differences between migrants born before 1931 and natives born before 1931, in the probability of completing 10 years of education, are negligible.

Figure 3.1 Estimated Probability of Completing 10 Years of Education for Different Age Groups. The birth cohorts have been binned into 6 groups. The 1923-26 and 1927-31 age groups comprise of migrants and natives who should have completed 10 years of education before 1947.



Since the pre-trends assumption holds, it makes sense to use the differences-in-differences approach for estimating the effect of the event (i.e. permanent displacement due to the partition of India and Pakistan). I will also discuss pre-trends assumption when I present the Results in the next section.

3.4.1 Threats to Identification

I will now discuss potential issues that can confound the estimates or threaten their causality.

Innate differences between migrants and natives: It is possible that migrants are systematically different from the domestic population of the residing country. For instance, parents of migrants might be more educated than the parents of natives. However, with a differences-in-differences type approach, this is not a concern for the causality of estimates as long as these differences are stable for individuals ages above 16 in 1947. In other words, the causality of the estimates will hold if the parallel trends assumption holds. Figure 1 indicates that these differences are stable for older cohorts. For individuals aged above 16 in 1947, I find no differences between migrants' and natives' likelihood to complete secondary education. Nonetheless, the pre-trends shown in Figure 1 may be questioned, owing to the recent developments in the literature. I will discuss these issues later in this section.

Systemically different birth cohorts: A common threat to identification would be that individuals born in a certain year were systematically different than individuals born in a different year and that these differences may be unobservable. To address this concern, I include birth year fixed effects instead of group cohort fixed effects as controls, in some specifications. The inclusion of birth cohort fixed effects is a powerful way to account for any unobserved differences across birth cohorts.

A related concern is that migrants who were less than 16 years of age in 1947 were different than older migrants, when they migrated in 1947. It is hard to empirically verify this claim but this will only hold true if something happened after 1931 that differentially affected all migrants born after 1931. To the best of my knowledge, there is no such evidence of a policy or a natural shock that will be of concern. Events like the Second World War, or the political changes in the years leading to the 1947 partition would affect the younger cohorts differently than the older cohorts but they will likely lead to a similar effect on both migrants and natives.

Selection of Migrants based on Who Migrated: A very important potential confounding factor could be that the violence during the event of the migration specifically targeted more (or less) able individuals and hence, the permanently displaced migrants were selected based on their ability or wealth or other characteristics. It is well established in the literature that the migration -and the associated mass scale violence- was based on religious motives (Bharadwaj et al. 2008). In other words, the perpetrators of violence did not choose their potential targets on the basis of the targets' abilities or educational qualifications. Muslims whose lives were under a greater threat in India due to violence in their districts were more likely to migrate regardless of their ability or educational preferences -the same was true for Hindus in Pakistan as well.

I provide some descriptive evidence in this regard, using data from the 1931 Census of British India and the 1951 post-partition Censuses of India and Pakistan. The census data contains information on the religious composition of the population in each district. In what became Pakistan, Sind and Punjab provinces share a boundary with India and saw out-migration of Hindus and Sikhs. From India, two states from which a considerable number of Muslims out-migrated to Pakistan were Uttar Pradesh (UP) and Punjab.

In Pakistan's Sind and Punjab, the change in percentage of Non-Muslim population in each district between 1931 and 1951 will be a proxy for the extent of out-migration. Similarly, the change in percentage Muslim population in each district in India's UP and Punjab will be a proxy for the extent of out-migration. The greater the reduction in the percentage of respective religious population in a district, the less likely it is that the migrants were selected based on education, wealth or other characteristics, and the more likely that they were forced to move out due to religious violence.

The main issue here is that, due to mass scale migration, the real population growth rate between 1931 and 1947 -i.e. before partition- is not known [5]. There is also no other reliable source of data available between 1931 and 1951 [6]. Simple difference in percentage of minority religious population in a district between 1931 and 1951 will not separate the changes in religious composition due population growth rate from the changes in religious composition due to migration.

However, the simple difference will most likely give us the lower bound of the actual difference. There are no major internal or external migration events or any other shocks that changed demographic composition within India between 1931 and 1947 (Bharadwaj et al. 2015) [7]. Moreover, it is known that the population growth rate for Muslims was slightly higher (Bharadwaj et al. 2015).

[5]Bharadwaj et al. (2015) employ two different methods to impute the population growth rate for the minority religious group's population in each district.

[6]There was a Census of British India in 1941 but its accuracy is highly questionable due to biased reporting in some regions and logistical issues around the time of the Second World War.

[7]Additionally, in the absence of migration, any positive or negative shocks affecting population growth shall not have differential effects across religious groups in a district.

Hence, at least for Muslims migrating out of Indian states of Punjab and UP, a simple decrease in percentage Muslim population in a district between 1931 and 1951 is likely lower than the actual decrease in the percentage Muslim population in a district.

Figure 2 plots the simple difference, in percentage minority population between 1931 and 1951, at district level. I calculate the minority population as a percentage of total population in 1931 and 1951, respectively, and then subtract the two values. Figure 2(a) plots the simple difference in percentage Non-Muslim population for districts in Sind and Punjab provinces of Pakistan. Figure 2(b) plots the simple difference in percentage Muslim population for districts in Punjab and UP states of India.

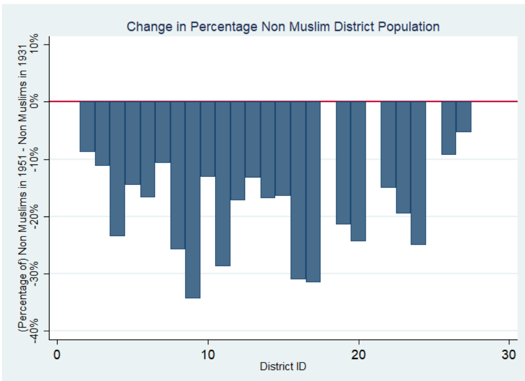
All districts in Pakistan's Sind and Punjab provinces experienced a decrease in percentage Non-Muslim population. No district experienced less than 5% decrease and three districts experienced greater than 30% decrease in their percentage of Non-Muslim population. In India's Punjab all districts experienced a decrease in Muslim population. Most of the 50 districts in the state of UP experienced a decrease in Muslim population. For the districts in UP which recorded an increase in the percentage Muslim population, the increase is very small and will probably vanish if we take into account the population growth between 1931 and 1947.

Hence, it can be argued that violence was not disproportionately targeted towards more (less) able individuals. In general, the violence was not based on any socioeconomic characteristics. Religious friction was single-handedly the largest driver of violence. Muslims living in minority as a district in India, and Hindus and Sikhs living as a minority in a district in Pakistan were most vulnerable to the religious violence. To aggravate the matters, Radcliff's erroneous methods for the border line resulted in millions finding themselves on the wrong side of the border.

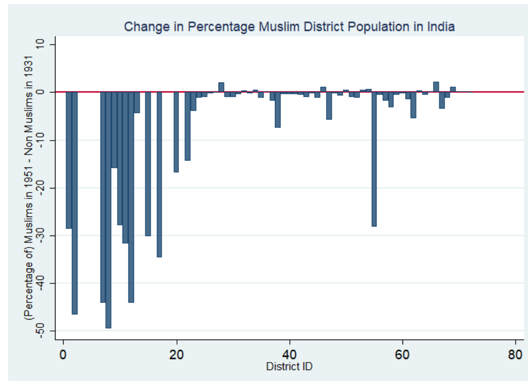
Thus, it is possible that Muslims were targeted in districts where they were in relative minority compared to Hindus (this would also hold true for Hindus located in Muslim majority areas in the current day Pakistan). However, a district is a large administrative identity and it would usually comprise of a distribution of individuals along literacy, wealth or other characteristics. Therefore, as long as the attacks were motivated by religious tensions, it is highly plausible that the acts of

Figure 3.2 Source: 1931 Census of British India, 1951 Censuses of India and Pakistan. In Figure a, Districts 1 through 17 are in Punjab and the remaining districts are in Sind. In Figure b, Districts 1 through 22 are in Punjab and the remaining districts are in Uttar Paradesh. As can be seen, data for some of the districts is not available, particularly for some districts in Indian Punjab.

(a) Change in percentage Non-Muslim population in districts of Punjab and Sind provinces in Pakistan



(b) Change in percentage Muslim population in districts of Punjab and Uttar Paradesh states in India



violence were selective only on the basis of religion. This implies, that within the population of Muslims based in India, the attacks carried out on them were random and not aimed at any particular subgroup within the Muslim community.

Selection of Migrants based on Where the Border was Drawn: We also know that Muslims based in Indian districts nearer to the Pakistan-India border were more likely to migrate than Muslims based in districts further away from the border (Bharadwaj et al. 2008). One potential threat could be that if the border was drawn along socioeconomic lines, it can confound the results. For instance, if the border was defined right next to the districts where literacy rates were high among Muslims, while the native population on the other side of the border comprised of a majority with little to no education, it would result in migrants being selectively different from the native population in terms of their educational preferences.

There is no evidence that the boundary carved out for between India and Pakistan was based on differential economic and/or educational outcomes. The border was drawn ostensibly along religious lines (Bharadwaj et al. 2008; Bharadwaj and Fenske 2012). As discussed in the Background section, the procedure of drawing the boundary surprised many by leaving them on the wrong side of the border. It is well known that the Muslim majority provinces of pre-partition India towards the North-West and West were demanded as a separate homeland for Muslims by the political party Muslim League purely on the basis of religious composition of the population in the region. In fact, distance from the border has been used as an instrument for research on agricultural productivity of migrants (Bharadwaj and Fenske 2012) which suggests that economic outcomes of interest such as productivity and individual ability are exogenous to distance from the border that was carved in 1947.

Differential rate of migration: Another minor point of concern could be that the differential rate of migration across different districts is driving the results. For instance, the district of Karachi is an outlier in the sense that it has more than 20% of its population classified as migrants in my sample. Bharadwaj et al. (2008) also report that the district of Karachi in Pakistan had 28% of its population classified as migrants in 1951. Another notable characteristic is that 91% of the literate population of the Karachi district in 1951 were migrants (Bharadawaj et al. 2008). However, local congestion of migrants would be accounted for by the district fixed effects. Hence, it is unlikely that congestion or differential rate of migration across different districts is driving the results.

Concerns Related to Staggered Treatment or Variation in Treatment Timing: The recent developments in the differences-in-differences literature also entail a discussion. First, identification in contexts with staggered treatment designs or selection in the timing of treatment have become a major source of concern in applied work that relies on differences-in-differences for identification (Goodman-Bacon 2021; Sun and Abraham 2020). However, the recent developments in this strand of literature are not a major source of concern because these concerns do not apply to the context here. Since the event took place once in 1947, everyone was exposed to the treatment at the same time. Hence, dynamic treatment effects or variation in treatment timing is not an issue. Second, as discussed in the Background section, the process of drawing the border line and the nature of the decision-making regarding the partition, on part of the British, rules out any anticipatory behavior where migrants could have moved earlier.

Concerns Related to Weights Assigned to Average Treatment Effect: Yet another strain of recent literature on differences-in-differences deals with the issues of weighting and confounds. In the presence of multiple groups, the treatment effect is a weighted estimate. In such a scenario, it is possible that the identified effect is negative but if the weights are also negative, one can also observe a positive treatment effect (Chaisemartin and D'Haultfoeuille 2022). Similarly, unobserved confounds correlated with the event and the outcome of interest may also confound the estimate (Freyaldenhoven et al. 2019). I address these concerns in the Robustness section.

Concerns Related to Low Statistical Power of Pre-Trends and Unobserved Confounds: Another recent development in this literature identifies the low statistical power of conventional pre-trends tests, and the subsequent exacerbation of bias in point estimates due to lower power (Rambachan and Roth 2022; Roth 2019). This is an important consideration because if the parallel-trends assumption only holds due to low statistical power, it voids the identification assumption. I discuss this issue and implement some empirical solutions offered by Roth (2019) in the Robustness section.

Similarly, unobserved confounds correlated with the event and the outcome of interest may also confound the estimate (Freyaldenhoven et al. 2019). I address both of these concerns in the Robustness section.

3.5 Results

In this section, I present the results from the estimation of equation 1 for three different outcome variables. These are indicator variables for completing 10 years of education, 5 years of education, and 12 years of education. The main outcome of interest is the indicator variable that equals 1 for individuals who have completed 10 years of education. I run three different specifications for each outcome variable.

Table 3 presents the results from estimation of equation 1. The outcome of interest is the indicator variable which equals 1 for individuals who have completed 10 years of education. Column 1 does not control for any controls except district fixed effects. Column 2 presents results from the fully specified model. Column 3 controls for all the covariates, but it includes individual year of birth fixed effects instead of group birth cohort fixed effects.

Table 3.3 Probability of Completion of 10 Years of Education for Different Migrant Birth Cohorts -relative to Natives.

Dependent Variable: =1 if completed 10 years of education	(1)	(2)	(3)
$Migrant * Birth_{1947-51}$	0.0859***	0.0782***	0.0856***
	(0.0124)	(0.0129)	(0.0129)
$Migrant * Birth_{1942-46}$	0.0668***	0.0459**	0.0436*
	(0.0171)	(0.0222)	(0.0222)
$Migrant * Birth_{1937-41}$	0.0376***	0.0230	0.0234
	(0.0126)	(0.0174)	(0.0175)
$Migrant * Birth_{1932-36}$	0.0307**	0.0125	0.0130
	(0.0143)	(0.0176)	(0.0174)
$Migrant * Birth_{1927-31}$	0.0237	0.0066	0.0075
	(0.0151)	(0.0162)	(0.0158)
$Migrant * Birth_{1923-26}$	0.0231*	0.0014	0.0018
	(0.0116)	(0.0126)	(0.0122)
Observations	425,441	425,441	425,441
R-squared	0.056	0.135	0.142
Individual Controls	Yes	No	Yes
Hh Controls	Yes	No	Yes
District Controls	Yes	No	Yes
District FE	Yes	Yes	Yes
Birth-Year FE	No	No	Yes

Standard errors clustered at district level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The parallel trends assumption holds for individuals who were older than 16 at the time of the partition in 1947. In both Columns 2 and 3, the coefficients for migrants who are in birth year groups 1923-26 and 1927-31 is very small and statistically not different from zero. This implies that migrants in these age cohorts are not very different from the natives in similar age cohorts in terms of their probability of completing 10 years of education.

In Column 1, the coefficient is positive for the oldest migrant individuals who were between 21 and 24 years of age in 1947, that is the 1923-26 birth year group. The coefficient size is not small and suggests that migrants were about 2.3 percentage points more likely to complete 10 years of education than their native counterparts. The coefficient size is about 2.4 percentage points for the 1927-31 birth year group.

However, the specification in column 1 does not control for anything other than district fixed effects, therefore, pointing to the likelihood that there is an omitted variable bias because characteristics like being in an urban area and household size etc. are likely to be correlated with being a migrant individual. This is evident from the fact that the R-squared for the specification in Column 2 is only 5.6% while it is 13.5% and 14.2% in Columns 2 and 3 respectively. In the subsequent discussion on the magnitudes of the coefficients, I will therefore only discuss coefficients from specifications in Columns 2 and 3.

In Columns 2 and 3, the coefficient for individuals belonging to the 1923-26 and 1927-31 age groups is not only statistically insignificant but it is also small in terms of its practical significance. The coefficient in Column 2 suggests that migrants belonging to the 1923-26 age group were only 0.14 percentage points more likely to complete 10 years of education than their native counterparts, while those in the 1927-31 age group were 0.6 percentage points more likely to complete 10 years of education than their native counter parts. These coefficients are many times smaller than the coefficients in Column 1.

Second, even for migrants who are in the school going age but are in the 1932-36 group (these would be individuals aged between 11 to 15 years in 1947), the coefficient is still not only very small but also not statistically different from zero. For migrants in the 1937-41 birth year group (these would be individuals aged between 6 to 10 years in 1947), the coefficient size is large enough to be of practical significance but it is still not statistically different from zero. Last, for migrants who were born after 1941 or were younger than 7 years at the time of partition, the coefficient is positive and statistically different from zero which implies that these individuals were more likely to complete secondary education than their native counterparts who were part of the same birth cohorts. This effect persists for migrant individuals born up until 4 years after the year of partition.

The coefficients in Table 3, for all the migrant individuals who were aged below 6 in 1947, entail a discussion. Specifically, this includes individuals in the birth year groups 1942-46 and

1947-51 -the individuals in the birth year group 1947-51 are those who were born during or after the event of partition took place. In Column 2, migrants in the birth year group 1942-46 cohort were 4.6 percentage points more likely to complete 10 years of education than the natives in the same birth year group. Column 3 has an almost identical coefficient.

These individuals in the 1942-46 birth year group would be aged between 1 and 5 years at the time of the partition. In other words, they migrated after being born, but were very less likely to have started their formal education before being permanently displaced. Given that the average age of completing 10 years of education is 16, the individuals enrolled in schools in 1947 would have most likely started their formal education after moving to Pakistan.

Hence, it is highly likely that migrant families -of migrant individuals who had not started their formal education in 1947- demanded more education for the children in their house and put a higher value on their children completing 10 years of education, relative to native families who already resided in Pakistan in 1947.

This interpretation is further substantiated by the coefficient size for migrants who belong to the birth year group 1947-51. The coefficient size for this birth year group is the largest among all six birth year groups. These individuals were born at the time of partition or after the partition. Hence, they would have started their formal schooling at least 5 years after the event of partition had taken place. According to Column 2 in Table 3, migrants belonging to this birth year group were about 7.8 percentage points more likely to complete 10 years of education than the native individuals in the same group. This coefficient size increases to about 8.6 percentage points in Column 3.

The younger cohorts, such as the individuals belonging to the 1947-51 birth year group, started their formal education a few years after the turbulent and violent event of partition had taken place. It can be safely assumed that most children start their first year of education at the age of 5-7 in most countries around the globe. Therefore, by the time these migrant individuals would have started their first year of formal education, their families were highly likely to have settled down with a relatively better access to basic needs such as food and shelter. This would imply that migrants in younger cohorts had a significantly greater access to schools and a better educational environment than migrants in older cohorts.

However, migrants belonging to the 1947-51 birth group cohort may be different from the others. As discussed previously, the bulk of migration happened between 1947 and 1951, and this group will contain migrants who migrated after been born in India. However, these migrants may be children of parents who decided to have a child after the partition of India and Pakistan had been announced, and had likely made the decision to migrate. Hence, this might be a very highly selected group. Hence, I will not be very confident in interpreting the coefficient for the migrants in this birth group cohort as solely a consequence of permanent displacement.

Hence, while the migrant individuals of school going age and their families placed a higher value on education, the younger migrants had an added advantage. They started their formal education in a much more stable, safe and peaceful environment with better access to basic needs such as food and shelter. Hence, the migrant individuals from younger birth year groups at the time of 1947 were much more likely to complete 10 years of education than their native counterparts.

In Column 2 in Table 3, migrants born in years 1942-46 are about 4.6 percentage points more likely to complete 10 years of education than native individuals in the same birth year group. This coefficient is almost twice the coefficient for the 1936-41 birth year group. The oldest cohort in this age group was 6 years old in 1947 which suggests that most of these individuals would not have started their formal education at the time of the partition. Hence, an important interpretation of the results emerges here: migrant individuals who had not started their formal schooling in 1947 are much more likely to complete 10 years of education that their native counterparts.

Comparatively, older migrant individuals faced a disruption in their formal schooling during the event of partition. Besides, the presence of certain issues immediately after permanent displacement such as access to a secure livelihood, food security and availability of shelter etc. would have further disrupted the access to educational infrastructure and the presence of an enabling environment for migrants belonging to older birth year groups. Hence, while older migrant individuals are indeed more likely to complete 10 years of education than their native counterparts, the magnitude of this increased likelihood is much smaller.

The coefficient size for individuals in the 1937-41 birth year cohort provides evidence in support of this argument. While it is not statistically different from zero at 90% significance level in Column 2 or Column 3, the coefficient in Column 2 suggests that migrant children belonging to this age group were 2.3 percentage points more likely to complete 10 years of education than their native counterparts. These individuals in the 1937-41 birth year group would be aged between 6 and 10 years at the time of the partition. Hence, the individuals enrolled in schools in 1947 would be in the process of completing their primary education at that time -primary education in Pakistan is defined as 5 years of education. It might be the case that if migrants belonging to this age group were successfully able to complete 5 years of education after being displaced, they might be more likely to outperform their native counterparts in completing 10 years of education, just like the younger cohorts.

Furthermore, in Tables 4 and 5 respectively, I also present results from the estimation of equation 1 but with an outcome variable that equals 1 if 5 years of education have been completed and an outcome variable that equals 1 if 12 years of education have been completed, respectively. I run the same three specifications I have used above in Table 3.

If individuals aged above 16 in 1947 are classified as those who have completed 10 years of education, individuals aged above 11 in 1947 will be classified as those who are above the average age at which 5 years of education is completed. Hence, all individuals born before 1936 were above the average age at which 5 years of education is completed. For these migrant individuals born before 1936, a coefficient that is statistically not different from zero implies that the parallel trend assumption holds.

The results for birth year groups 1923-26, 1927-31 and 1932-26 in Columns 2 and 3 of Table 4 indeed suggest that parallel trend assumption does hold. The coefficients are very small in magnitude and they are not statistically different from zero.

The results in Table 4 are similar in interpretation to the results presented in Table 3. Results in Table 4 show that for individuals belonging to the birth year groups 1942-46 and 1947-51, forced migration increased their probability of completion of education, relative to their native

Table 3.4 Probability of Completion of 5 Years of Education for Different Migrant Birth Cohorts -relative to Natives.

Dependent Variable: =1 if completed 5 years of education			
	(1)	(2)	(3)
$Migrant * Birth_{1947-51}$	0.1028***	0.0868***	0.0942***
	(0.0143)	(0.0178)	(0.0183)
$Migrant * Birth_{1942-46}$	0.1044***	0.0655**	0.0615**
	(0.0221)	(0.0293)	(0.0293)
$Migrant * Birth_{1937-41}$	0.0639***	0.0326	0.0329
	(0.0182)	(0.0270)	(0.0272)
$Migrant * Birth_{1932-36}$	0.0649***	0.0274	0.0278
	(0.0209)	(0.0262)	(0.0258)
$Migrant * Birth_{1927-31}$	0.0569***	0.0201	0.0214
	(0.0202)	(0.0241)	(0.0233)
$Migrant * Birth_{1923-26}$	0.0529***	0.0126	0.0129
	(0.0161)	(0.0193)	(0.0187)
Observations	425,441	425,441	425,441
R-squared	0.069	0.195	0.205
Individual Controls	Yes	No	Yes
Hh Controls	Yes	No	Yes
District Controls	Yes	No	Yes
District FE	Yes	Yes	Yes
Birth-Year FE	No	No	Yes

Standard errors clustered at district level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

counterparts in the same birth cohorts. Once again, the coefficient size is larger for the migrants in the birth year group 1947-51.

The results presented in Table 5, where the probability of completion of 12 years of education is estimated, reinforce the interpretation of the results discussed in this section. Individuals who started their formal schooling after being displaced, and hence, did not experience a disruption while attending school, are more likely to complete 12 years of education than their native counterparts. For migrants who were receiving formal education at the time of being permanently displaced, the coefficient is always positive but it is not statistically different from zero. The size of the coefficient is of practical significance however, particularly for the 1937-41 birth year group.

Table 3.5 Probability of Completion of 12 Years of Education for Different Migrant Birth Cohorts -relative to Natives.

Dependent Variable: =1 if completed 12 years of education			
	(1)	(2)	(3)
$Migrant * Birth_{1947-51}$	0.0621***	0.0603***	0.0650***
	(0.0074)	(0.0087)	(0.0082)
$Migrant * Birth_{1942-46}$	0.0355***	0.0276*	0.0258
	(0.0127)	(0.0157)	(0.0156)
$Migrant * Birth_{1937-41}$	0.0186**	0.0147	0.0149
	(0.0083)	(0.0110)	(0.0110)
$Migrant * Birth_{1932-36}$	0.0099	0.0042	0.0045
	(0.0076)	(0.0100)	(0.0098)
$Migrant * Birth_{1927-31}$	0.0054	0.0006	0.0012
	(0.0098)	(0.0101)	(0.0098)
$Migrant * Birth_{1923-26}$	0.0067	-0.0016	-0.0013
	(0.0056)	(0.0058)	(0.0056)
Observations	425,441	425,441	425,441
R-squared	0.033	0.079	0.085
Individual Controls	Yes	No	Yes
Hh Controls	Yes	No	Yes
District Controls	Yes	No	Yes
District FE	Yes	Yes	Yes
Birth-Year FE	No	No	Yes

Standard errors clustered at district level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.6 Robustness Analysis

3.6.1 Sensitivity Analysis

One particular concern is that the average age defined for completion of 10 years of education is arbitrary. The global average age for starting first year of formal education is 5-7 years. This implies that an individual should be able to complete 10 years of education by the time they are aged 15-17 years -assuming there is no discontinuity in their educational process.

I had assumed the average age of completion of 10 years of education is 16 years. However, there is no state enforced age restriction on enrollment in schools in Pakistan, although some private educational institutions themselves may impose such restrictions. Furthermore, there is a potential concern that forced migrants might have had disruption in their educational process and they might have completed their education later. Hence, the arbitrary definition of 16 years of age for completion of secondary education can be a problem.

However, in the discussion in the previous section, the coefficient for migrant individuals from the birth year groups 1927-31 was not only very small in magnitude but it was also not statistically different from zero. In other words, migrant individuals who were aged between 16 and 20 at the time if partition in 1947 did not do any better in terms of the probability of completion of 10 years of education than native individuals of the same birth year group. Hence, this result holds for individuals much older than 16 at the time of partition in 1947. This result provides strong evidence in favor of the point that the arbitrary definition of 16 years as average of completion of 10 years of education does not really affect our results.

To substantiate this evidence further, I define the average age of completion of 10 years of education at 18 years and I conduct the same analysis again. Individuals above 18 years of age in 1947 would be those individuals who were born up until 1929. I classify the individuals into four birth year groups or bins: 1923-29, 1930-36, 1937-43 and 1944-51. The birth year group 1923-29 contains individuals who were aged above 18 in 1947. These are the individuals aged between 18 and 24 in 1947.

A coefficient that is not statistically different from zero for migrants from the 1923-29 birth year group would lend further strength to the claim that the arbitrary definition of an age for completion of 10 years of education does not matter.

The results are presented in Table 6. As expected, the coefficient for the migrants who belong to the 1923-29 birth group is not statistically different from zero in Columns 2 and Column 3. Hence, the parallel trends assumption required for identification still holds.

The results in Table 6 are comparable to the results presented in Table 3 in the previous section. The coefficient sizes and the interpretation of the results does not change. Migrants belonging to the birth year group 1944-51 have the largest coefficient size. The coefficient for the migrants who belong to the 1930-36 birth group is not statistically different from zero in Columns 2 and 3.

Table 3.6 Robustness Check: Average age of completion of 10 years of education defined as 18 instead of 16.

Dependent Variable: =1 if completed 10 years of education			
	(1)	(2)	(3)
$Migrant * Birth_{1944-51}$	0.0669***	0.0562**	0.0690***
	(0.0182)	(0.0229)	(0.0232)
$Migrant * Birth_{1937-43}$	0.0425***	0.0276	0.0281
	(0.0123)	(0.0174)	(0.0176)
$Migrant * Birth_{1930-36}$	0.0304*	0.0135	0.0140
	(0.0149)	(0.0178)	(0.0176)
$Migrant * Birth_{1923-29}$	0.0226*	0.0023	0.0031
	(0.0122)	(0.0135)	(0.0132)
Observations	425,441	425,441	425,441
R-squared	0.057	0.135	0.142
Individual Controls	Yes	No	Yes
Hh Controls	Yes	No	Yes
District Controls	Yes	No	Yes
District FE	Yes	Yes	Yes
Birth-Year FE	No	No	Yes

Standard errors clustered at district level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient for the migrant individuals in the 1930-36 birth year group is smaller than for the two younger birth year groups. In Column 2, the migrants in this birth group cohort were about 1.3 percentage points point more likely to complete 10 years of education than their native counterparts. In Table 3 where the coefficient for the migrant individuals in the 1932-26 birth year group was not statistically different from zero, but the size of both coefficients is comparable. Combined, both these results suggest that migrant individuals aged above 12, albeit still of school going age, did not perform much better at attaining certain educational outcomes, when compared with their native counterparts.

Additionally, the coefficient for the 1937-43 birth year group in Column 2 of Table 6 suggests that migrants were 2.8 percentage points more likely to complete 10 years of education than their native counterparts. This coefficient is just marginally statistically insignificant at 90% significance level. In terms of size, it is very comparable to the coefficient for the 1937-41 birth year group in Table 3.

Column 2 of Table 6 shows that migrant individuals in the 1944-51 birth year group are about 5.6 percentage points more likely to complete 10 years of education than their native counterparts. This coefficient however, is about two thirds the size of the coefficient in Table 3 for the 1947-51 birth year group but is slightly larger than the coefficient in Table 3 for the 1942-46 birth year group.

Using the redefined birth group cohorts in this section, I present similar results with an outcome variable that equals 1 if 5 years of education have been completed and an outcome variable that equals 1 if 12 years of education have been completed, respectively. The results are presented in Tables E1 and E2 in the Appendix E, respectively. The qualitative interpretation of the results remains the same, suggesting that the results are robust to changes in assumptions about when certain education milestones are completed.

3.6.2 Low Statistical Power and Unobserved Confounds

Roth (2019), and Rambachan and Roth (2022) show that conventional pre-trends in a differences-in-differences may suffer with the problem of low statistical power. Additionally, Roth (2019) shows that in the presence of low statistical power for identifying pre-trends, the bias in post-event point estimates of treatment effect aggravates. This issue becomes less severe with more pre-event time periods but more severe with more post-event time periods.

Roth and Rambachan (2022) provide the package HonestDiD in R for implementing their methods and for testing the power of pre-trends. I intend to implement their methods as part of future work on this paper.

It must also be noted that my sample size is very large, with more than 400,000 observations, and hence, the issue of low statistical power might not be of a huge concern. However, I do perform two other analysis which help address this concern.

In the original estimation described in equation 1, there were two pre-event birth cohort groups and four post-event birth cohort groups. Hence, the lower number of pre-event time periods and greater number of post-event time periods will exacerbate the bias in post-event point estimates of treatment effect, if there is a problem of low statistical power in identification of pre-trends.

To address this concern, I aggregate the number of group cohorts in my study, in two ways. The first method creates a simple two period study where the first time period is pre-event and the second time period is post-event. In this context, the former refers to all individuals above 16 years of age in 1947, or equivalently, those born before 1931. In the second method, I keep the two pre-event birth cohort groups as it is, but I aggregate the four post-event group cohorts into one. In other words, everyone born after 1931 is treated as one birth cohort group.

The second method in particular has two pre-event time periods and one post-event time period. Hence, if the pre-trends or parallel trends assumption still holds with this empirical strategy, and if the post-event point estimate of the treatment is comparable to the point estimates presented in Table 3, then the issue of low statistical power and associated bias is alleviated to a great extent.

The results are presented in Table 7. Columns 1 and 2 present the results from a two period study design (one pre-event and one post-event), and Columns 3 and 4 present the results from a three period study design (two pre-event and one post-event). First, and most important, the pre-trends hold in all the Columns. This is considerably strong evidence that our pre-trends do not exist due to low statistical power. Second, the permanent displacement does still increase the probability of completion of 10 years education for migrants who were of school going age, relative to their native counterparts.

Next, I turn to the issue of potential confounds. Freyaldenhoven et al. (2019) discuss the issue of unobservable confounds that are correlated to both the event and the outcome of interest, thus contaminating the point estimates of the treatment effect. In the context of this paper, one potential confounding factor could be the pre-partition literacy rate in areas that became Pakistan in 1947. If natives historically came from areas with lower literacy rates, then my identification strategy captures the effect of lower literacy among migrants rather than the effect of forced migration from India to Pakistan. In other words, it can be that the difference in historical literacy level and the difference in demand for education between migrants and natives are confounding the estimates. The pre-trends assumption is satisfied in my main estimation as well as in the robustness checks in this section, but it fails to directly control for historical literacy differences.

Table 3.7 Reducing the number of post-event time periods

Dependent Variable: =1 if completed 10 years of education

	(1)	(2)	(3)	(4)
	Two Period		Three Period	
$Migrant * Birth_{1932-51}$	0.0305***	0.0299***	0.0345*	0.0348*
	(0.0089)	(0.0095)	(0.0196)	(0.0201)
$Migrant * Birth_{1923-31}$	0.0041	0.0049		
	(0.0142)	(0.0139)		
$Migrant * Birth_{1927-31}$			0.0064	0.0076
			(0.0161)	(0.0157)
$Migrant * Birth_{1923-26}$			0.0014	0.0019
			(0.0125)	(0.0122)
Observations	425,441	425,441	425,441	425,441
R-squared	0.135	0.142	0.135	0.142
Individual Controls	Yes	Yes	Yes	Yes
Hh Controls	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Birth-Year FE	No	Yes	No	Yes

Standard errors clustered at district level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To address this issue I plan to use information from the 1931 Census of British India and 1951 Census of Pakistan to control for (a) literacy rate in 1931, and (b) the number of literate migrants from India in each district in 1951. These results will be added to this paper as part of the future work. I am still collecting raw data from these Census on literacy by age, gender, and region.

3.6.3 Weights Assigned to Average Treatment Effect

This section addresses the concerns in the recent differences-in-differences literature that are discussed by Chaisemartin and D'Haultfoeuille (2020), and Chaisemartin and D'Haultfoeuille

(2022). In the presence of multiple groups and/or multiple treatment periods, the treatment effect is a weighted estimate. In such a scenario, it is possible that the identified effect is negative but if the weights are also negative, one observes a positive treatment effect (Chaisemartin and D'Haultfoeuille 2022). Similarly, unobserved confounds correlated with the event and the outcome of interest may also confound the estimate (Freyaldenhoven et al. 2019). I address these concerns in the Robustness section.

Chaisemartin and D'Haultfoeuille (2020) outline the procedure for dealing with such a situation. The first step is to check if the weights are indeed negative. If all the weights are positive, then the estimates do not suffer from this concern [8]. Chaisemartin and D'Haultfoeuille (2020) provide a Stata package called twowayfeweights for this purpose. In my checks, all the specifications returned zero negative weights and all positive weights. Hence, this is not a major source of concern for the treatment effects identified and discussed in this paper.

3.7 Mechanisms

As discussed in the Introduction section, partition was a broad phenomenon which resulted in demographic changes, mass violence, casualties, end of colonial era, new governments, the birth of a new country and an increased religious homogeneity on both sides of the newly carved out border. Hence, there were many different mechanisms at play which could have led to the results discussed in the last section. Besides, the paucity of data does not allow me to empirically explore some potential mechanisms.

However, theory and applied research in development microeconomics present testable hypothesis for understanding the potential link between permanent displacement of school going migrants and their higher likelihood of completing certain educational milestones. The classical literature mostly looks at rural-urban migration (Harris and Todaro 1970; Todaro 1986), and migration networks(Munshi 2003; Munshi and Rosenzweig 2016; Swee 2017). Some research work also identifies migrants having a higher demand for education (Brenner and Kiefer 1981).

[8] If the negative weights are indeed the culprit behind a positive treatment effect, Chaisemartin and D'Haultfoeuille (2020) provide methods and accompanying Stata packages for estimating treatment effects in this situation.

Broadly, two themes may help explain the higher educational attainment of migrants. These are (a) the decisions taken by migrants and (b) the change in their behavior due to forced migration. The former focuses on location decisions, while the latter looks at migrants' higher demand for education as opposed to material gains (Becker et al. 2020).

3.7.1 Location Decisions

Developing countries typically see a rural-urban migration pattern because of depressed wages in the rural sector and better socioeconomic opportunities in urban areas (Todaro 1986). The same phenomenon may induce permanently displaced migrants to settle in urban centers. It is known that migrants from India to Pakistan -and from Pakistan to India- in 1947 were willing to travel greater distances to settle into urban centers. Bharadwaj et al. (2008) term this the "big city effect."

In addition, the government of Pakistan had allotted lands to the migrants (Bharadwaj and Mirza 2019). While migrants received agricultural land particularly in the province of Punjab, a substantial number of migrants settled in the city of Karachi which was the national capital at that time as well as the financial hub. This is reflected by the fact that 28% of Karachi's population in 1951 comprised of migrants.

Were the migrants who chose to move to urban areas different from migrants who were allotted agricultural land or who chose to settle in rural areas? It is plausible that educated migrants decided to move to cities like Karachi [9].

The population of interest in this paper is migrants of school going age or those who were aged below 16 when they migrated. They possibly could not have made the location decision on their own. The older migrants most likely made the location decision. If it is indeed true that older migrants who settled into urban centers were more literate than the native population, it can help explain the younger cohorts' higher likelihood to achieve certain educational milestones. This is because these urban areas or major cities were more likely to offer better educational opportunities

[9] Karachi was also an outlier because 91% of its literate population comprised of migrants! (Bharadwaj et al. 2015).

by providing better infrastructure as well as a convenient environment through easier access to schooling.

It must be noted, however, that choosing an urban center as a destination does not imply differential access to resources, schooling, or employment opportunities when compared to the native population. It does, however, imply easier access to schooling when compared to rural areas. It also implies that migrants in urban centers had to seek non-agricultural occupations. Non-agricultural occupations are more likely to require skills, and hence, literacy, compared to agricultural occupations -particularly in developing countries where low skilled labor is typically employed by the agricultural sector.

As part of the future work on this paper, I plan to present two pieces of evidence in this regard. The 1951 Census Data contains information on the number of non-agricultural workers in each tehsil [10] by gender. Information is also available for the number of migrants in each occupation. I plan to split the main sample into urban and rural regions, and then collapse the sample at tehsil level. The coefficient of interest will be percentage of migrant population in urban and rural regions in each district, respectively. I expect to see an increase in the percentage of urban tehsil population working in non-agricultural occupations, as a result of migration.

Second, I plan to use the data on literacy available in the 1951 Census to explore whether literate older migrants were more likely to settle in urban areas. Specifically, I will see if proportion of migrants in the urban area within a district increased tehsil literacy rates.

This is an important channel that would have helped younger cohorts achieve higher educational goals. Being in urban areas of metropolitan cities increases the access to educational infrastructure. It also provides more enabling environment for getting education. For forced migrants, a convenient environment for pursuing education can be very important in completing certain educational milestones (Gould et al. 2004).

I also check for a third potential mechanism related to location decisions. In developing countries with limited social support from the state, living with extended family can also act

[10]Tehsil is an administrative level below district.

as an important social support. This becomes particularly crucial in the context of this paper because Pakistan's nascent government had limited resources at its disposal to aid the migrants. For young individuals of school going age, living with extended family has important consequences for educational achievements. It can partially reduce the pressure of ensuring that basic needs are met and, thus, ensure that a conducive environment for pursuing educational goals is available.

Table 8 presents results from an estimation with the dependent variable that equals 1 if an individual is living with the extended family. This time, fully specified equation 1 is estimated. None of the coefficients is statistically different from zero for any of the birth year groups with individuals younger than 16 years of age in 1947. However, the coefficients are positive for all individuals born after 1937. Hence, there is some evidence that individuals who migrated were more likely to be living with extended family in 1973 than their native counterparts. This would suggest that a stronger cushion was available to migrants in the form of informal social protection from extended family. Stronger social support is likely to allow migrant individuals to pursue education, without shouldering the responsibility of contributing to family earnings, relative to their native counterparts.

3.7.2 Demand for Education

The second mechanism explores the possibility that migrants and their families placed a higher value on education. While I do not have relevant data to explore this empirically, this holds enough importance in the literature to warrant a discussion.

The literature on educational outcomes of migrants does suggest that migrants tend to have a higher demand for education (Brenner and Kiefer 1981; Becker et al. 2020). More importantly, Becker et al. (2020) show that descendants of Polish migrants who were forcibly displaced during the Second World War had a higher demand for education relative to descendants of both voluntary migrants and natives. Becker et al. (2020) also found evidence in support of the "uprootedness hypothesis" which is essentially a shift in preferences towards investment in education instead of investment in physical capital. They found that people with migrant ancestors not only had higher

Table 3.8 Social Support in the Form of Living with Extended Family

Extended family as social support	
	(1)
	Dependent Variable:
	= 1 if living with extended family
$Migrant * Birth_{1947-51}$	-0.0042
	(0.0107)
$Migrant * Birth_{1942-46}$	0.0111
	(0.0096)
$Migrant * Birth_{1937-41}$	0.0072
	(0.0048)
$Migrant * Birth_{1932-36}$	0.0007
	(0.0043)
$Migrant * Birth_{1927-31}$	-0.0042
	(0.0063)
$Migrant * Birth_{1923-26}$	0.0164***
	(0.0049)
Observations	388,464
R-squared	0.341
Individual Controls	Yes
Hh Controls	Yes
District Controls	Yes
District FE	Yes

Standard errors clustered at district level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

educational aspirations but they also owned fewer assets than what they could afford.

Hence, in the context explored by Becker et al. (2020), migration shifted the preferences towards investment in education and away from material possessions. This shift in preferences can be founded on a number of underlying reasons including, but not limited to, an increase in subjective probability of negative economic shocks in the future so that education may serve as an insurance, a shift in the willingness to take risks and a shift in discount rates associated with returns on education.

Brenner and Kiefer (1981), in their pioneering study on the economics of diaspora, also point out three reasons why the migrants may have more incentives to invest in human capital. These include (1) the migrants being initially more educated which contributes to an increase in human capital accumulation, (2) occupational discrimination against migrants, and (3) even if there is a decline in this discrimination overtime, the investment in human capital continues due to the patterns of human capital accumulation by parents or older generations.

While the paucity of data does not allow me to explore if the forcibly displaced migrants in the context studied in this paper also had a higher demand for education, the fact that Becker et al. (2020) found that forcibly displaced migrants had a higher demand for education than voluntary migrants has important implications for this study. Violence was a major determinant of migratory outflows (Jha and Wilkinson 2012) and individuals in districts with more violence were more likely to migrate. As discussed earlier, partition of British India, the subsequent migration along religious lines and the civil war that ensued formed a chaotic and violent episode in the history of the Indian subcontinent. While the true estimate is unknown, it is well established that millions of people died due to mass violence during partition and migration. Bharadwaj et al. (2015) estimate that at least 2.2 million people went missing while migrating between Pakistan and India.

The sequence of events faced by forcibly displaced migrants in this context is comparable to the events faced by Polish migrants, as described by Becker et al. (2020). Following Brenner and Kiefer (1981), one similarity that exists in both set of migrants is the discrimination faced in the past, which might lead to higher demand for education. Specifically, it is the discrimination faced in the past. In the context studied in this paper, it is inherently the religious discrimination and violence on the basis of religion that compelled the migrants to move to a different country.

Brenner and Kiefer (1981) also show that migrants being initially more educated contributes to an increase in human capital investment. In the context studied in this paper, there is evidence that at least migrants who chose to settle in urban areas were more literate than their native urban counterparts. Additionally, districts which received a large proportion of migrants saw an increase in their literacy rates immediately as a consequence of migration (Bharadwaj et al. 2015). Refugee presence in Indian districts was indeed found to be correlated with increased literacy (Bharadwaj and Mirza 2019). Hence, this could be another reason that migrants from India had a higher demand for education than their native counterparts.

Another important finding in the Results section suggested that migrants from older birth year groups of school going age did not do any better than the natives from the same birth year groups. Specifically, migrant individuals in the 1932-36 age group -or the individuals aged between 12 and 16 years in 1947- did not do any better than the native individuals of the same age group in terms of their likelihood of completing 5, 10 or 12 years of education.

However, given the above discussion on migrants' higher demand for education and the "up-rootedness hypothesis", it will be incorrect to assume that older migrant individuals of school going age did not do better than their native counterparts because they did not value education as highly as younger migrant individuals did. Instead, their inability to complete more education is likely to be the consequence of permanent displacement, food insecurity, search for a secure livelihood and struggle for a certain degree of stability in living standards. Unfortunately, the paucity of the data does not allow me to explore this possibility empirically.

Intuitively, migrants were starting their lives from scratch and the opportunity cost of forgoing work in order to attain education was very high, at least for the initial few years. This is likely to have significant consequences for individuals who were in the school going age but were relatively older; they would have contributed more to the household's utility through participation in the labor market than through pursuance of education. In other words, the opportunity cost of education for older migrant cohorts was very high. This can help explain why younger migrant individuals were able to achieve better educational outcomes relative to their native counterparts, but older migrant individuals still of school going age were not able to do the same relative to their native counterparts.

While I do not have empirical evidence to support the claim that migrants had a higher demand for education, the similarities in the experiences faced by the migrants studied in this paper, and the migrants studied by Becker et al. (2020) warranted a thorough discussion on this potential mechanism. There is a high likelihood that the discrimination faced by the migrants, and the experience of being permanently displaced and moving to a new country changed their preferences for education and human capital investment.

3.8 Conclusion

In this study, I considered the educational outcomes of individuals who were forced to migrate from one country to another. Forced migration is an important issue in both historical and modern times. The United Nations estimates that more than 80 million people are currently forcibly displaced due to wars, conflicts and natural disasters (UNHCR 2020).

In line with the other findings in the literature, I find that migrants are more likely to complete certain educational milestones, than their native counterparts. This suggests that, while the immediate consequences of forced migration is very dramatic, the migrants can achieve better outcomes relative to the native population in the presence of a stable, peaceful and enabling environment.

What differentiates these migrants from those studied previously in the literature is is that they lacked any state support. They had immigrated into a newborn country which was facing a political and constitutional crisis, lacked basic educational infrastructure, had just emerged out of a wide-scale violent episode of partition and had millions of migrants to accommodate. Even in the face of this adversity, migrant children were able to perform much better than their native counterparts.

In this process, the migrants may have been facilitated by their decision to migrate to big cities and urban areas, and by their decision to choose non-agricultural occupations. However, it is also highly likely that migrants' preferences shifted away from investment in physical capital to investment in education. This could have been due to their experience of migration and permanent displacement which was filled with violence and discrimination. In the literature, this "uprooted hypothesis" has been found to be an important channel that can help explain the higher educational aspirations of migrants relative to the native population.

Additionally, settling in urban areas or major urban centers of Pakistan would have increased the access to educational facilities for migrants. Coupled with the fact that migrants placed a higher value on education or had a higher demand for education, better access to educational infrastructure allowed the younger migrants to surpass their native counterparts in terms of completing high school education.

These findings would suggest that the migrants may also do significantly better than their native counterparts on the labor market later in their lives. Unfortunately, the census surveys conducted after 1973 do not provide information on country of birth which does not allow me to investigate this empirically. However, Duflo (2001) did find that the Indonesian school building program (INPRES) led to an increase of 3 to 5.4 percent in wages through a 12 percent increased probability that a child would complete primary school.

In our estimates, the younger migrants were about 4-8 percentage points more likely to complete primary schooling or 5 years of education. While the context here is totally different -I look at a negative economic shock for the migrating families in the form of forced migration while Duflo (2001) looks at a positive economic shock in the form of a school building program- the results from Duflo (2001) can be extrapolated to get an idea of the performance of migrants on labor market relative to their native counterparts. Assuming that the results from Duflo (2001) can hold in our context, my estimates suggest an increase of about 1.5 to 2.5 percent in wages.

This study holds importance for migrating children of school going age around the globe. It suggests that as long as these migrants can settle in a stable and peaceful environment, they are highly likely to outperform their native counterparts in educational attainment. In the pursuit of better education, migrant individuals of school going age are likely to be undeterred by difficulties such as lack of state support, permanent displacement of masses, limited educational infrastructure and the pressure of securing a livelihood.

The challenges pointed out in the last paragraph can, however, partially hinder their ability to attain certain educational milestones. This explains why older migrants who were still of school going age do not do better than their native counterparts in terms of educational attainment. Nonetheless, the availability of a stable and peaceful environment can ensure that at least some, if not all, migrants of school going age have a higher propensity to attain education than their native counterparts.

An important conclusion from the discussion in this paper is that the migrant and permanently displaced individuals do not require a lot of state support for pursuing their educational goals -although policy interventions designed to help migrants might have led to even better performance of migrants. Thus, this study points out at the importance of ensuring peace and stability in the lives of migrants and permanently displaced people around the globe. If policy makers can, at the minimum, ensure a peaceful and stable environment for permanently displaced individuals, these individuals can achieve higher educational milestones. As seen in the context studied in this paper, this holds true even for large scale permanent displacement of communities.

I must also point out the limitations of this study. Partition was a multi-dimensional event which had demographic, social and economic consequences discussed before. Hence, there are many different mechanisms and channels at play and it will be incorrect to interpret the results solely as a consequence of partition. Moreover, the discussion in the Mechanisms section should particularly be taken with a pinch of salt. The paucity of data does not allow me to explore certain potential mechanisms. Besides, given the nature of partition, many important channels driving the results might have been missed out.

Nonetheless, the findings reported here are important because they show that individuals who have been forced to migrate have higher educational aspirations and achieve better educational outcomes even when the receiving country's government can only offer limited support. Most of the literature finds that negative shocks in the early life have a negative affect on the later educational and labor market outcomes (Singhal 2018; Maccini and Yang 2010; Galdo 2013; Leon 2012). However, forced migrants are able to not only nullify the negative affect of a negative shock in the early stages of their lives but they are also able to achieve better educational outcomes than their native counterparts.

This study only concentrates on estimating the educational achievements of the migrants. However, the changes in educational preferences of migrants is very likely to have had broader impacts on the Pakistani economy. How did the economy respond to a shock in the supply of educated workers in the long run? Studying these effects can be a potential objective of future research work related to migration.

APPENDICES

APPENDIX A

APPENDIX A FOR CHAPTER 1

A.1 Appendix A

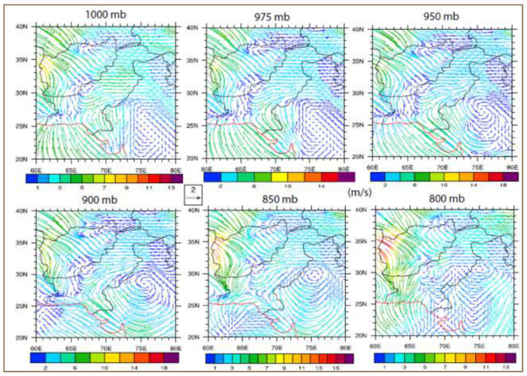
Table A.1 Summary statistics for variables used in this paper.

Mean and Std. Deviation of variables

	(1) N	(2) mean	(3) sd
Total Crime	611	1,301	1,574
Total Violent Crime	611	549.5	330.8
Total Non-Violent Crime	611	6,337	7,764
Mean Daily Air Pollution in Winter Months	684	2,126	1,798
Mean Daily Air Pollution in Rest of the Year	684	1,935	1,768
Annual Mean Daily Air Pollution	684	2,005	1,741
Mean Daily No. of Fires in Residue Burning Season	684	37.35	70.31
Mean Daily No of Fires in Rest of the Year	684	29.47	28.05
Annual Mean Daily No of Fires	684	32.13	26.88
Temperature (Celsius) in Winter Months	684	15.37	1.207
Precipitation (Millimeters per Day) in Winter Months	684	0.839	0.637
Rice Production (Thousands of Tonnes)	544	95.19	117.5
Rice Area (Thousands of Hectares)	544	50.33	59.83
Mean Wind Direction in Rice Growing Districts	19	-0.684	0.199
District Area	36	5,801	4,326
District Population	36	3.056e+06	2.016e+06
Mean Distance from Rice Growing Districts	36	171.6	91.90
Weighted Latitude	36	0.993	0.0410

Figure A.1 Source: FAO (2018)

(a) Wind Direction and Wind Speed during October in Pakistan



(b) Wind Direction and Wind Speed during January in Pakistan

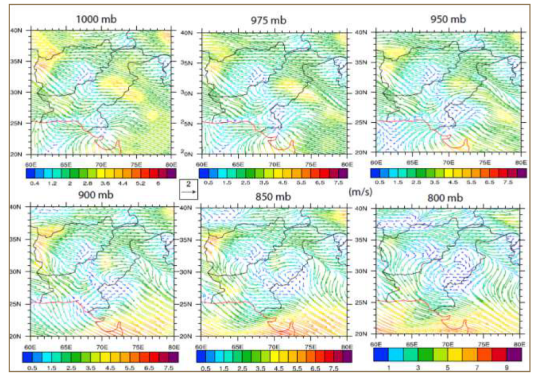


Figure A.2 Provinces of Pakistan: Punjab can be seen at North and Center East

Figure A.3 A Flow Chart of the Events Leading to an Increase in Crime

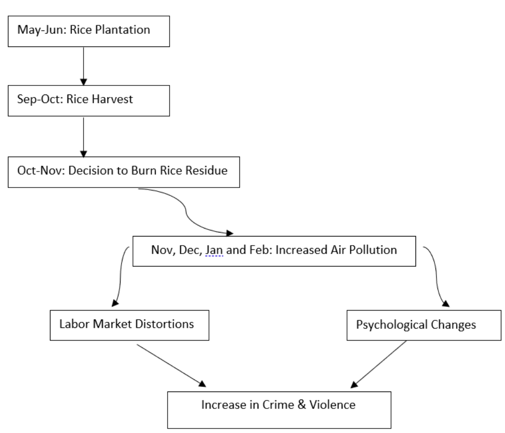


Table A.2 First stage results (additional specifications for robustness).

Air Pollution in the Winter Months				
	(1)	(2)	(3)	(4)
	First Stage	First Stage	First Stage	First Stage
			Lagged Effects	
Wind_Distance	-0.00283***	-0.00266***	-0.00298***	-0.00283***
	(0.00054)	(0.00060)	(0.00055)	(0.00057)
Kleibergen-Paap F stat	27.47	19.49	29.22	24.50
Observations	611	611	575	574
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Rice Controls	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No
Avg. Instrument	1262	1262	1262	1262
Avg. Air Pollution	2126	2126	2126	2126

Robust standard errors in parentheses

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

Notes: The results are from the first stage estimation of equation 1.2. The dependent variable is the average air pollution in months of November, December, January and February. The instrument is the wind direction -as explained in the paper- for the months October, November and December. Columns 3 and 4 are results from the IV regression of crime on lagged air pollution and hence, they lose one year of observations. The standard errors are clustered at district level.

Table A.3 First stage results (specifications with additional controls).

	Air Pollution in the Winter Months			
	(1)	(2)	(3)	(4)
	First Stage	First Stage	First Stage	First Stage
			Lagged Effects	
Wind_Distance	-0.00277***	-0.00277***	-0.00293***	-0.00277***
	(0.00066)	(0.00068)	(0.00060)	(0.00068)
Kleibergen-Paap F stat	17.77	16.69	23.64	16.69
Observations	490	428	428	428
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	Yes	Yes	Yes	Yes
Rice Controls	No	Yes	No	Yes
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Avg. Instrument	1262	1262	1262	1262
Avg. Air Pollution	2126	2126	2126	2126

Robust standard errors in parentheses

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

Notes: The results are from the first stage estimation of equation 1.2. The dependent variable is the average air pollution in months of November, December, January and February. The instrument is the wind direction -as explained in the paper- for the months October, November and December. Columns 3 and 4 are results from the IV regression of crime on lagged air pollution and hence, they lose one year of observations. Columns 1 and 3 include data on district level socioeconomic controls. Columns 2 and 4 additionally include data on rice production, rice area as well. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level.

Table A.4 First stage results (specifications with dependent variable weighted by population).

	Air Pollution in the Winter Months			
	(1)	(2)	(3)	(4)
	First Stage	First Stage	First Stage	First Stage
			Lagged Effects	
Wind_Distance	-0.00283***	-0.00277***	-0.00298***	-0.00277***
	(0.00054)	(0.00068)	(0.00055)	(0.00068)
Kleibergen-Paap F stat	18.53	16.36	16.66	11.40
Observations	490	428	428	428
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Rice Controls	No	Yes	No	Yes
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Avg. Instrument	1262	1262	1262	1262
Avg. Air Pollution	2126	2126	2126	2126

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

Notes: The results are from the first stage estimation of equation 1.2. The dependent variable is the average air pollution in months of November, December, January and February. The instrument is the wind direction -as explained in the paper- for the months October, November and December; weighted by the rice sown with rice crop in the 12 rice growing districts in the year 2002. Columns 3 and 4 are results from the IV regression of crime on lagged air pollution and hence, they lose one year of observations. Columns 2 and 4 include data on rice production, rice area and other district level controls. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level.

Table A.5 OLS estimation results for the effect of air pollution on crime.

Log of Annual Violent Crimes per 1000 Sq. Km					
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
			Lagged Effects		
AOD_w_{jt} (Standardized)	0.03712**	0.02477	0.03551**	0.01795	0.00885
	(0.01903)	(0.01468)	(0.01691)	(0.01258)	(0.01351)
Bootstrap P-value	[.04905]	[.10110]	[.03704]	[.14815]	[.46947]
District FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes	Yes
Rice Controls	No	No	No	No	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No	Yes
Observations	611	611	575	574	428
R-squared	0.915	0.924	0.922	0.934	0.965
Avg. Air Pollution	2126	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801	5801
Avg. Crime	549.5	549.5	550.4	550.4	550.4

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

Notes: The results are from the OLS estimation of equation 1.1. The dependent variable is the log of annual violent crime in a district weighted by district area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 through 5 estimate the lagged effects of air pollution in the four winter months on crime. Columns 5 includes rice production controls and other district level controls. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table A.6 OLS estimation results for the effect of air pollution on crime.

Log of Annual Non-Violent Crimes per 1000 Sq. Km

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
			Lagged Effects		
Wind_Distance	0.00035	-0.00854	-0.00476	-0.01703	-0.00308
	(0.01230)	(0.01123)	(0.01502)	(0.01428)	(0.01350)
Bootstrap P-value	[.97798]	[.43143]	[.76777]	[.26727]	[.82883]
District FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes	Yes
Rice Controls	No	No	No	No	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No	Yes
Observations	611	611	575	574	428
R-squared	0.972	0.975	0.974	0.977	0.979
Avg. Air Pollution	2126	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801	5801
Avg. Crime	6337	6337	6423	6423	6423

Robust standard errors in parentheses

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

Notes: The results are from the OLS estimation of equation 1.1. The dependent variable is the log of annual non-violent crime in a district weighted by district area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 through 5 estimate the lagged effects of air pollution in the four winter months on crime. Columns 5 includes rice production controls and other district level controls. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table A.7 Reduced form estimation results.

Log of Annual Violent Crimes per 1000 Sq. Km

	(1) Reduced Form	(2) Reduced Form	(3) Reduced Form	(4) Reduced Form	(5) Reduced Form
				Lagged Effects	
Wind_Distance	0.00060*	0.00040	0.00074**	0.00060***	0.00048**
	(0.00036)	(0.00030)	(0.00025)	(0.00022)	(0.00022)
Bootstrap P-value	[.06406]	[.17518]	[.01101]	[.00701]	[.03103]
District FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes	Yes
Rice Controls	No	No	No	No	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No	Yes
Observations	611	611	575	574	428
R-squared	0.916	0.924	0.923	0.934	0.969
Avg. Instrument	1262	1262	1262	1262	1262
Avg. Area(2017)	5801	5801	5801	5801	5801
Avg. Crime	549.5	549.5	550.4	550.4	550.4

Robust standard errors in parentheses

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

Notes: The results are from the estimation of the reduced form in equation 1.3. The dependent variable is the annual violent crime in a district weighted by district area. The instrument is the wind direction -as explained in the paper- for the months October, November and December; weighted by the rice sown with rice crop in the 12 rice growing districts in the year 2002. Columns 3 and 4 are results from the IV regression of crime on lagged air pollution and hence, they lose one year of observations. Columns 2 and 4 include data on rice production, rice area and other district level controls. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table A.8 Main estimation equation results (with crime weighted by district population).

Log of Annual Violent Crimes per 100000 People				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
			Lagged Effects	
AOD_w_{jt} (Standardized)	0.27400	0.21780***	0.44575**	0.17498**
	(0.45761)	(0.07445)	(0.19509)	(0.07215)
Bootstrap P-value	[.51051]	[.00300]	[.02302]	[.01401]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Rice Controls	No	Yes	No	Yes
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	No	Yes	No	Yes
Observations	611	428	575	428
R-squared	0.431	0.807	0.414	0.840
Avg. Air Pollution	2126	2126	2126	2126
Avg. Pop(2017)	3.056e+06	3.056e+06	3.056e+06	3.056e+06
Avg. Crime	549.5	549.5	550.4	550.4

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual violent crime in a district weighted by district population. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. Columns 2 and 4 include division-specific time trend, other district level controls and additionally control for rice production variables. The data on rice production is not available for 2018, and the data on district level socio-economic variables is not available for 2017. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table A.9 Main estimation equation results (with crime weighted by district population).

Log of Annual Violent Crimes per 1000 Sq. Km				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
			Lagged Effects	
AOD_w_{jt} (Standardized)	0.26747**	0.20139	0.28310***	0.24312**
	(0.11640)	(0.12862)	(0.10445)	(0.11150)
Bootstrap P-value	[.00400]	[.11111]	[.00501]	[.01201]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Weather Controls	Yes	Yes	Yes	Yes
Observations	611	611	575	574
R-squared	0.905	0.918	0.907	0.922
Avg. Air Pollution	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801
Avg. Crime	549.5	549.5	550.4	550.4

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

Notes: The results are from the instrumental variable estimation of equation 1.1. For building the instrument, the definition of rice growing districts is changed and the 11 rice growing districts identified in FAO's (2018) report are considered as the rice growing districts. The dependent variable is the log of annual violent crime in a district weighted by area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

APPENDIX B

APPENDIX B FOR CHAPTER 1

B.1 Appendix B

Table B.1 First stage results with modified instrument.

Air Pollution in the Winter Months

	(1)	(2)	(3)	(4)
	First Stage	First Stage	First Stage	First Stage
			Lagged Effects	
$Wind\_Distance$	-0.00065***	-0.00061***	-0.00069***	-0.00065***
	(0.00012)	(0.00014)	(0.00013)	(0.00013)
Kleibergen-Paap F stat	27.47	19.49	29.22	24.50
Observations	611	611	575	574
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Rice Controls	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No
Avg. Instrument	5464	5464	5464	5464
Avg. Air Pollution	2126	2126	2126	2126

Robust standard errors in parentheses

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

Note: The results are from the first stage estimation of equation 1.2. The dependent variable is the average air pollution in months of November, December, January and February. The instrument is the wind direction -as explained in the paper- but additionally weighted by the inverse of the predicted rice area of the rice growing districts. Columns 3 and 4 are results from the IV regression of crime on lagged air pollution and hence, they lose one year of observations. The standard errors are clustered at district level.

Table B.2 A placebo test with Western districts assumed as rice growers.

Log of Annual Violent Crimes per 1000 Sq. Km				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
			Lagged Effects	
AOD_w_{jt} (Standardized)	1.03931	1.04584	22.36030	39.61717
	(1.24748)	(1.22289)	(320.94970)	(1,123.60466)
Bootstrap P-value	[.23323]	[.31331]	[.90791]	[.39239]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Division-Specific Trend	No	Yes	No	Yes
Rice Controls	No	No	Yes	No
Weather Controls	Yes	Yes	Yes	Yes
Other Controls	No	No	Yes	No
$Wind\_Distance$	0.00012	0.00012	-0.00000	-0.00000
	(0.00011)	(0.00011)	(0.00011)	(0.00012)
First Stage F-stat	1.1655	1.1976	.00439	.00109
Observations	611	611	575	574
R-squared	0.904	0.920	0.913	0.928
Avg. Air Pollution	1935	1935	1935	1935
Avg. Area(2017)	5801	5801	5801	5801
Avg. Crime	549.5	549.5	550.4	550.4

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual violent crime in a district weighted by district area. The main explanatory variable of interest, AOD_w_{jt},is standardized. Columns 3 and 4 estimate the lagged effects of air pollution in the four winter months on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table B.3 Heterogeneity by type of violent crime.

	Log of Annual Crimes per 1000 Sq. Km				
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
	Attempted Murder	Assault	Kidnapping	Murder	Rape
AOD_w_{jt} (Standardized)	0.18674**	0.18551**	0.16797	0.21613***	0.41794***
	(0.08846)	(0.06719)	(0.10360)	(0.05848)	(0.13539)
Bootstrap P-value	[.03904]	[.01401]	[.15215]	[0.00000]	[.00400]
District FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Division-Specific Trend	No	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes	Yes
Observations	603	603	603	603	603
R-squared	0.952	0.945	0.904	0.968	0.899
Avg. Air Quality	2126	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801	5801
Avg. Crime	180.1	549.2	317.7	147.7	63.09

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual crime in a district weighted by district area. Each specific type of crime is Presented in a different column. The main explanatory variable of interest, AOD_w_{jt},is standardized. All columns estimate the contemporaneous effect of air pollution on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table B.4 Heterogeneity by type of violent crime (lagged effect).

	Attempted Murder	Assault	Kidnapping	Murder	Rape
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
	Attempted Murder	Assault	Kidnapping	Murder	Rape
AOD_w_{jt} (Standardized)	0.25594***	0.25649***	0.16797	0.30170***	0.24330*
	(0.09956)	(0.08209)	(0.10360)	(0.10139)	(0.13036)
Bootstrap P-value	[.00200]	[.00200]	[.15215]	[.00200]	[.09710]
District FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Division-Specific Trend	No	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes	Yes
Observations	575	575	575	575	575
R-squared	0.868	0.903	0.904	0.893	0.847
Avg. Air Quality	2126	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801	5801
Avg. Crime	180.1	549.2	317.7	147.7	63.09

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

Notes: The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual crime in a district weighted by district area. Each specific type of violent crime is presented in a different column. The main explanatory variable of interest, AOD_w_{jt},is standardized. All columns estimate the lagged effect of air pollution on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table B.5 Heterogeneity by type of non-violent crime.

	Log of Annual Crimes per 1000 Sq. Km				
	(1) IV Dacoity	(2) IV Robbery	(3) IV Burglary	(4) IV Vehicle Theft	(5) IV Ordinary Theft
AOD_w_{jt} (Standardized)	0.13266	-0.05630	0.10817	0.11593	0.24370**
	(0.14878)	(0.13449)	(0.15218)	(0.11294)	(0.09502)
Bootstrap P-value	[.38138]	[.66366]	[.50250]	[.31932]	[.01602]
District FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Division-Specific Trend	No	No	No	No	No
Weather Controls	Yes	Yes	Yes	Yes	Yes
Observations	603	603	603	602	603
R-squared	0.911	0.956	0.909	0.965	0.934
Avg. Air Quality	2126	2126	2126	2126	2126
Avg. Area(2017)	5801	5801	5801	5801	5801
Avg. Crime	52.31	377.7	321.6	403.3	737.3

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

The results are from the instrumental variable estimation of equation 1.1. The dependent variable is the log of annual crime in a district weighted by district area. Each specific type of non-violent crime is presented in a different column. The main explanatory variable of interest, AOD_w_{jt},is standardized. All columns estimate the lagged effect of air pollution on crime. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table B.6 The effect of air pollution on seasonal employment.

	= 1 If Unemployed			
	(1) IV 23 < Age ≤ 30	(2) IV 30 < Age ≤ 40	(3) IV 35 < Age ≤ 50	(4) IV 50 < Age≤ 60
AOD_w_{jt} (Standardized)	-0.04041**	-0.03007	0.01186	-0.03560
	(0.02891)	(0.03191)	(0.02016)	(0.03509)
Bootstrap P-value	[.04204]	[.20621]	[.49850]	[.16216]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Observations	50,593	55,278	45,030	27,770
Avg. Air Pollution	2311	2311	2311	2311

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

Notes: The results are from the instrumental variable estimation of equation 1.5. The dependent variable a dummy variable that equals 1 if the individual is employed. The main explanatory variable of interest, AOD_w_{jt},is standardized. The instrument is the wind direction -as explained in the paper. The explanatory variable is the interaction of the air pollution variable with a dummy that equals 1 for the four winter months. Only male individuals are considered. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table B.7 Increase in violence as a potential mechanism.

= 1 If Justifies Violence Towards Wife	
	(1)
	IV
AOD_w_{jt} (Standardized)	-0.29240
	(0.36236)
Bootstrap P-value	[.24224]
Observations	23,999
R-squared	0.013
District FE	Yes
Time FE	Yes
Weather Controls	Yes
Observations	23,999
R-squared	0.013
Avg. Air Pollution	2311

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

The results are from the instrumental variable estimation of equation 1.5. The dependent variable a dummy variable that equals 1 if an individual justifies violence towards their spouse. The main explanatory variable of interest, AOD_w_{jt},is standardized. The instrument is the wind direction -as explained in the paper. The explanatory variable is the interaction of the air pollution variable with a dummy that equals 1 for the four winter months. Only male individuals are considered. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses

APPENDIX C

APPENDIX C FOR CHAPTER 2

C.1 Appendix C

Table C.1 OLS estimation results for the effect of terrorist attacks on earnings.

Dependent Variable: Log Real Monthly Income		
	(1)	(2)
Annual District Attacks	0.00027	-0.00078
	(0.00097)	(0.00166)
Bootstrap P-value	[0.807]	[0.617]
Observations	98,313	98,313
R-squared	0.378	0.411
District FE	Yes	Yes
Time FE	Yes	Yes
Weighted by Fatalities	Yes	Yes
Avg. Attacks	16.03	16.03
Avg. Log Income	8.561	8.561

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

Notes: The results are from the OLS regression of equation 2.10. The dependent variable is the log of real monthly income. The main explanatory variable of interest is the annual district attacks. Columns 3 and 4 exclude observations that reported annual earnings. Columns 2 and 4 include district fixed effects instead of the time-invariant distance variable. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table C.2 The effect of terrorist attacks on earnings (by timing of attacks).

Dependent Variable: Log Real Monthly Income	
	(1)
	IV
Annual District Attacks	-0.00027
	(0.00166)
Bootstrap P-value	[0.883]
Observations	49,938
R-squared	0.379
District FE	Yes
Time FE	Yes
Weighted by Fatalities	Yes
Avg. Attacks	3.398
Avg. Log Income	8.562

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

Notes: The results are from the IV regression of equation 2.10. The dependent variable is the log of real monthly income. The main explanatory variable of interest is the annual district attacks. The sample only includes individuals who did not experience an attack in the month in which they were observed. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table C.3 The effect of terrorist attacks on earnings (additional specifications for robustness).

Dependent Variable: Log Real Monthly Income		
	(1)	(2)
Annual District Attacks	-0.00104	-0.00182**
	(0.00178)	(0.00084)
Bootstrap P-value	[0.637]	[0.0561]
Observations	98,313	76,810
R-squared	0.411	0.458
District FE	Yes	Yes
Time FE	Yes	Yes
Weighted by Fatalities	Yes	Yes
Avg. Attacks	16.03	16.03
Avg. Log Income	8.561	8.561

Robust standard errors in parentheses
Standard errors are clustered at district level
*** p<0.01, ** p<0.05, * p<0.1

Notes: The results are from the IV regression of equation 2.10, with the addition of log of sample size by year-district-birth year group as a control. The dependent variable is the log of real monthly income. The main explanatory variable of interest is the annual district attacks. Column 2 excludes individuals that reported annual earnings.

Table C.4 The effect of terrorist attacks on earnings (additional specifications by timing of attacks).

Dependent Variable: Log Real Monthly Income

	(1)	(2)	(3)
Panel A: All Observations			
Annual District Attacks	-0.00321	-0.00414*	-0.00290
	(0.00206)	(0.00240)	(0.00219)
Bootstrap P-value	[0.338]	[0.335]	[0.359]
Observations	62,919	56,992	53,271
R-squared	0.424	0.435	0.440
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes
Panel B: Excluding Observations Reporting Annual Incomes			
Annual District Attacks	-0.00359***	-0.00428***	-0.00373***
	(0.00095)	(0.00118)	(0.00119)
Bootstrap P-value	[0.0110]	[0.0230]	[0.0200]
Observations	42,159	36,448	32,808
R-squared	0.465	0.475	0.483
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes
Avg. Attacks	44.13	58.59	76.64

Notes: The results are from the IV regression of equation 2.10. The dependent variable is log of real monthly income. The main explanatory variable of interest is the annual attacks in each district with the addition of log of sample size by year-district-birth year group as a control. Column 1 includes individuals whose district faced at lease one attack in the month they were observed. Columns 2 and 3 restrict the sample further to individuals whose district experienced an attack in the previous one month and previous two months respectively, in addition to the current month. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

Table C.5 Being sick or injured as a potential mechanism.

Dependent Variable: =1 if Sick or Injured

	(1)	(2)	(3)
Annual District Attacks	0.00008	0.00011	-0.00006
	(0.00021)	(0.00021)	(0.00022)
Bootstrap P-value	[0.701]	[0.627]	[0.792]
Observations	114,155	112,969	80,239
R-squared	0.018	0.018	0.018
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Weighted by Fatalities	Yes	Yes	Yes
Avg. Attacks	14.94	17.50	46.55
Proportion Sick/Injured	0.0749	0.0749	0.0749

Robust standard errors in parentheses

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

Notes: The results are from the IV regression of equation 2.10. The dependent variable is a dummy that equals 1 if an individual reported to be sick or injured in the last two weeks. The main explanatory variable of interest is the annual attacks in each district. Columns 2 excludes observations that reported annual earnings while Column 3 restricts samples to individuals who experienced a terrorist attack in their district in the same month when they were observed. The standard errors are clustered at district level. The p-values from the wild cluster bootstrap method are presented in square parentheses.

APPENDIX D

APPENDIX D FOR CHAPTER 2

D.1 Appendix D

PSLSM classifies occupations into the following categories: senior officials, professionals, clerks, sales, skilled agriculture, crafts and trade, plant operations, and elementary occupations. While the details of which jobs fall under each categorization are provided in the manual, a further breakdown is not available in the first 4 rounds of the data which is why we do not use a detailed breakdown in our analysis.

Senior Officials: This includes legislators, senior government officials, village heads, corporate managers, general managers, and armed forces personnel.

Professionals: This category includes physical, mathematical, and engineering science professionals, health professionals (doctors, nurses etc.), teachers, and other professionals such as librarians, writers, artists etc.

Technicians and Associate Professionals: These include professions such as ship and aircraft controllers, life science technicians, traditional medical health workers, teaching associate professionals and primary school teachers, business service agents, trade brokers, police inspectors, customs officials etc [1].

Clerks: This category includes secretaries, operating clerks, numerical clerks, transportation clerks, cashiers, tellers, customer service agents etc.

Sales: This is a broad category which comprises of travel attendants, restaurant services, housekeeping, personal care, sales workers, stall workers, demonstrators, market sales persons etc.

Skilled Agriculture: This category includes crop growers, animal producers, forestry workers, fishery workers, hunters, and subsistence agriculture and fishery workers.

Crafts and Trades: These comprise of miners, stonecutters, building finishers, welders, metal molders, blacksmiths, tool makers, mechanics, electricians, potters, glass makers, handicraft workers, cabinet makers, shoemakers, food processing and related trade workers, textile workers etc.

Plant and Machine Operators: This category includes mining and mineral processing, metal processing, ceramics, chemical processing, wood processing, power production, automated assem-

[1] Since there is overlap between this and the preceding category, we group them as a single occupational classification.

bly line workers, machinery operators in textiles and other sectors, locomotive engine drivers etc.

Elementary Occupations: The last category category includes street vendors, shoe cleaning and other similar services, domestic and related helpers, cleaners and launderers, messengers, door-keepers, garbage collectors, and laborers in agriculture, fisheries and mining, construction workers, transportation workers, laborers in manufacturing etc.

APPENDIX E

APPENDIX E FOR CHAPTER 3

E.1 Appendix E

Table E.1 Robustness Check: Average age of completion of 5 years of education defined as 11.

Dependent Variable: =1 if completed 5 years of education			
	(1)	(2)	(3)
$Migrant * Birth_{1944-51}$	0.0934***	0.0693**	0.0803***
	(0.0200)	(0.0276)	(0.0287)
$Migrant * Birth_{1937-43}$	0.0726***	0.0413	0.0420
	(0.0178)	(0.0262)	(0.0265)
$Migrant * Birth_{1930-36}$	0.0646***	0.0277	0.0278
	(0.0215)	(0.0267)	(0.0263)
$Migrant * Birth_{1923-29}$	0.0544***	0.0155	0.0162
	(0.0170)	(0.0206)	(0.0201)
Observations	425,441	425,441	425,441
R-squared	0.070	0.196	0.204
Individual Controls	Yes	No	Yes
Hh Controls	Yes	No	Yes
District Controls	Yes	No	Yes
District FE	Yes	Yes	Yes
Birth-Year FE	No	No	Yes

Standard errors clustered at district level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.2 Robustness Check: Average age of completion of 12 years of education defined as 20.

Dependent Variable: =1 if completed 12 years of education			
	(1)	(2)	(3)
$Migrant * Birth_{1944-51}$	0.0458***	0.0433**	0.0498***
	(0.0143)	(0.0171)	(0.0173)
$Migrant * Birth_{1937-43}$	0.0201**	0.0160	0.0161
	(0.0081)	(0.0111)	(0.0113)
$Migrant * Birth_{1930-36}$	0.0086	0.0040	0.0043
	(0.0085)	(0.0105)	(0.0104)
$Migrant * Birth_{1923-29}$	0.0065	-0.0009	-0.0004
	(0.0063)	(0.0069)	(0.0068)
Observations	425,441	425,441	425,441
R-squared	0.034	0.079	0.085
Individual Controls	Yes	No	Yes
Hh Controls	Yes	No	Yes
District Controls	Yes	No	Yes
District FE	Yes	Yes	Yes
Birth-Year FE	No	No	Yes

Standard errors clustered at district level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

BIBLIOGRAPHY

BIBLIOGRAPHY

Abadie, A. and Gardeazabal, J. (2003). The economic costs of conflict: A case study of the basque country. *American Economic Review*, 93(1):113–132.

Abubakar, S. M. (2016). Pakistan 5th most vulnerable country to climate change, reveals germanwatch report. *Dawn*.

Acemoglu, D., Hassan, T. A., and Robinson, J. A. (2011). Social structure and development: A legacy of the holocaust in russia. *The Quarterly Journal of Economics*, 126(2):895–946.

Adelaja, A. and George, J. (2019a). Effects of conflict on agriculture: Evidence from the boko haram insurgency. *World Development*, 117:184 – 195.

Adelaja, A. and George, J. (2019b). Terrorism and land use in agriculture: The case of boko haram in nigeria. *Land Use Policy*, 88:104116.

Adhvaryu, A. and Nyshadham, A. (2016). Endowments at birth and parents' investments in children. *The Economic Journal*, 126(593):781–820.

Agnew, R. (2001). Building on the foundation of general strain theory: Specifying the types of strain most likely to lead to crime and delinquency. *Journal of Research in Crime and Delinquency*, 38(4):319–361.

Ali, Z. (2015). Idps to start returning to their areas tomorrow. *Dawn*.

Almond, D. (2006). Is the 1918 influenza pandemic over? long-term effects of in utero influenza exposure in the post-1940 u.s. population. *Journal of Political Economy*, 114(4):672–712.

Almond, D. and Currie, J. (2011). Killing me softly: The fetal origins hypothesis. *Journal of Economic Perspectives*, 25(3):153–72.

Anderson, C. A. and Bushman, B. J. (2002). Human aggression. *Annual Review of Psychology*, 53(1):27–51. PMID: 11752478.

Angrist, J. D. and Krueger, A. B. (1995). Split-sample instrumental variables estimates of the return to schooling. *Journal of Business & Economic Statistics*, 13(2):225–235.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly Harmless Econometrics*. Princeton University Press.

APP (2015). Idps to start returning to their areas tomorrow. *Dawn*.

Archsmith, J., Heyes, A., and Saberian, S. (2018). Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. *Journal of the Association of Environmental and Resource Economists*, 5(4):827–863.

Banerjee, A. and Iyer, L. (2005). History, institutions, and economic performance: The legacy of colonial land tenure systems in india. *American Economic Review*, 95(4):1190–1213.

Beatty, T. K. and Shimshack, J. P. (2014). Air pollution and children's respiratory health: A cohort analysis. *Journal of Environmental Economics and Management*, 67(1):39–57.

Becker, G. S. (1968). *Crime and Punishment: an Economic Approach*, pages 13–68. Palgrave Macmillan UK, London.

Becker, S. O., Grosfeld, I., Grosjean, P., Voigtlander, N., and Zhuravskaya, E. (2020). Forced migration and human capital: Evidence from post-wwii population transfers. *American Economic Review*, 110(5):1430–63.

Behrman, J. R. and Rosenzweig, M. R. (2004). Returns to birthweight. *Journal of Economics and Statistics*, 86(2):586–601.

Bennett, S., Farrington, D. P., and Huesmann, L. R. (2005). Explaining gender differences in crime and violence: The importance of social cognitive skills. *Aggression and Violent Behavior*, 10(3):263–288.

Berkowitz, L. (1989). Frustration-aggression hypothesis: Examination and reformulation. *Psychological bulletin*, 106(1):59–73.

Bharadwaj, P. and Ali Mirza, R. (2019). Displacement and development: Long term impacts of population transfer in india. *Explorations in Economic History*, 73:101273.

Bharadwaj, P. and Fenske, J. (2012). Partition, migration, and jute cultivation in india. *The Journal of Development Studies*, 48(8):1084–1107.

Bharadwaj, P., Khwaja, A. I., and Mian, A. (2008). The big march: Migratory flows after the partition of india. *Economic and Political Weekly*, 43(35):39–49.

Bharadwaj, P., Khwaja, A. I., and Mian, A. (2015). Population exchange and its impact on literacy, occupation and gender – evidence from the partition of india. *International Migration*, 53(4):90–106.

Bharadwaj, P., Khwaja, A. I., and Mian, A. (June 2009). The partition of india: Demographic consequences. *SSRN*.

Blakeslee, D. S. and Fishman, R. (2018). Weather Shocks, Agriculture, and Crime Evidence from India. *The Journal of Human Resources*, 53(3):750–782.

Blundell, R., Graber, M., and Mogstad, M. (2015). Labor income dynamics and the insurance from taxes, transfers, and the family. *Journal of Public Economics*, 127:58–73. The Nordic Model.

Bondy, M., Roth, S., and Sager, L. (2020). Crime is in the air: The contemporaneous relationship between air pollution and crime. *Journal of the Association of Environmental and Resource Economists*, 7(3):555–585.

Borusyak, K., Hull, P., and Jaravel, X. (2021). Quasi-Experimental Shift-Share Research Designs. *The Review of Economic Studies*, 89(1):181–213.

Brenner, R. and Kiefer, N. M. (1981). The economics of the diaspora: Discrimination and occupational structure. *Economic Development and Cultural Change*, 29(3):517–534.

Burkhardt, J., Bayham, J., Wilson, A., Berman, J. D., O'Dell, K., Ford, B., Fischer, E. V., and Pierce, J. R. (2020). The relationship between monthly air pollution and violent crime across the united states. *Journal of Environmental Economics and Policy*, 9(2):188–205.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, 90(3):414–427.

Campaniello, N. and Gavrilova, E. (2018). Uncovering the gender participation gap in crime. *European Economic Review*, 109:289–304. Gender Differences in the Labor Market.

Carr, J. B. and Packham, A. (2019). SNAP Benefits and Crime: Evidence from Changing Disbursement Schedules. *The Review of Economics and Statistics*, 101(2):310–325.

Chamarbagwala, R. and Morán, H. E. (2011). The human capital consequences of civil war: Evidence from guatemala. *Journal of Development Economics*, 94(1):41 – 61.

Chaney, E. and Hornbeck, R. (2016). Economic dynamics in the malthusian era: Evidence from the 1609 spanish expulsion of the moriscos. *The Economic Journal*, 126(594):1404–1440.

Charlton, D., James, A., and Smith, B. (2021). Seasonal agricultural activity and crime. *American Journal of Agricultural Economics*.

Coccaro, E. F., Sripada, C. S., Yanowitch, R. N., and Phan, K. L. (2011). Corticolimbic function in impulsive aggressive behavior. *Biological Psychiatry*, 69(12):1153 – 1159. Prefrontal Cortical Circuits Regulating Attention, Behavior and Emotion.

Covell, C. N. and Scalora, M. J. (2002). Empathic deficits in sexual offenders: An integration of affective, social, and cognitive constructs. *Aggression and Violent Behavior*, 7(3):251–270.

Cruz, E., D'alessio, S. J., and Stolzenberg, L. (2021). Air Pollution and Violent Criminal Behaviour. *The British Journal of Criminology*, 62(2):450–467.

Currie, J. (2001). Early childhood education programs. *Journal of Economic Perspectives*, 15(2):213–238.

Currie, J. and Almond, D. (2011). Chapter 15 - human capital development before age five. In Card, D. and Ashenfelter, O., editors, *Handbook of Labor Economics*, volume 4, pages 1315 – 1486. Elsevier.

Currie, J., Stabile, M., Manivong, P., and Roos, L. L. (2010). Child health and young adult outcomes. *Journal of Human Resources*, 45(3):517 – 548.

Currie, J. and Vogl, T. (2013). Early-life health and adult circumstance in developing countries. *Annual Review of Economics*, 5(1):1–36.

Currie, J. and Walker, R. (2011). Traffic congestion and infant health: Evidence from e-zpass. *American Economic Journal: Applied Economics*, 3(1):65–90.

de Chaisemartin, C. and D'Haultfoeuille, X. (2022). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. Working Paper 29691, National Bureau of Economic Research.

Dell, M. (2010a). The persistent effects of peru's mining mita. *Econometrica*, 78(6):1863–1903.

Dell, M. (2010b). The persistent effects of peru's mining mita. *Econometrica*, 78(6):1863–1903.

Dell, M. and Olken, B. A. (2017). The development effects of the extractive colonial economy: The dutch cultivation system in java. Working Paper 24009, National Bureau of Economic Research.

Dell, M. and Querubin, P. (2017). Nation Building Through Foreign Intervention: Evidence from Discontinuities in Military Strategies. *The Quarterly Journal of Economics*, 133(2):701–764.

Dippel, C. (2014). Forced coexistence and economic development: Evidence from native american reservations. *Econometrica*, 82(6):2131–2165.

Draca, M., Koutmeridis, T., and Machin, S. (2018). The Changing Returns to Crime: Do Criminals Respond to Prices? *The Review of Economic Studies*, 86(3):1228–1257.

Duflo, E. (2001). Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American Economic Review*, 91(4):795–813.

Duflo, E. and Pande, R. (2007). Dams*. *The Quarterly Journal of Economics*, 122(2):601–646.

Duque, V. (2017). Early-life conditions and child development: Evidence from a violent conflict. *SSM - Population Health*, 3:121 – 131.

Edmark, K. (2005). Unemployment and crime: Is there a connection? *The Scandinavian Journal* *of Economics*, 107(2):353–373.

Ehrlich, I. (1973). Crime, punishment, and the market for offenses. *Journal of Economic Perspectives*, 10(1):43–67.

FAO (2018). Remote sensing for spatio-temporal mapping of smog in punjab and identification of the underlying causes using gis techniques. Report, Food and Agricultural Organization of the United Nations.

for Asylum, E. A. (2016). Easo country of origin information report: Pakistan security situation. Technical report, European Asylum Support Office.

Foster, A., Gutierrez, E., and Kumar, N. (2009). Voluntary compliance, pollution levels, and infant mortality in mexico. *American Economic Review*, 99(2):191–97.

Freedman, M. and Owens, E. G. (2016). Your Friends and Neighbors: Localized Economic Development and Criminal Activity. *The Review of Economics and Statistics*, 98(2):233–253.

Freyaldenhoven, S., Hansen, C., and Shapiro, J. M. (2019). Pre-event trends in the panel event-study design. *American Economic Review*, 109(9):3307–38.

Galdo, J. (2013). The long-run labor-market consequences of civil war: Evidence from the shining path in peru. *Economic Development and Cultural Change*, 61(4):789–823.

Garces, E., Thomas, D., and Currie, J. (2002). Longer-term effects of head start. *American Economic Review*, 92(4):999–1012.

Garg, T., McCord, G. C., and Montfort, A. (2020). Can social protection reduce environmental damages. *SSRN*.

George, J., Adelaja, A., and Weatherspoon, D. (2020). Armed conflicts and food insecurity: Evidence from boko haram's attacks. *American Journal of Agricultural Economics*, 102(1):114–131.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

González-Guevara, E., Martínez-Lazcano, J. C., Custodio, V., Hernández-Cerón, M., Rubio, C., and Paz, C. (2014). Exposure to ozone induces a systemic inflammatory response: possible source of the neurological alterations induced by this gas. *Inhalation Toxicology*, 26(8):485–491.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277. Themed Issue: Treatment Effect 1.

Gottfredson, M. and Hirschi, T. (1990). *A General Theory of Crime*. Stanford University Press.

Gould, E. D., Weinberg, B. A., and Mustard, D. B. (2002). Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997. *The Review of Economics and Statistics*, 84(1):45–61.

Graff Zivin, J. and Neidell, M. (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management*, 58(2):119–128.

Graff Zivin, J. and Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7):3652–73.

Greenstone, M. and Fan, Q. (2019). Pakistan's air pollution challenge and potential for longer lives. Report, Air Quality Life Index (AQLI) and Energy Policy Institute at The University of Chicago.

Grossman, D., Khalil, U., and Ray, A. (2019). Terrorism and early childhood health outcomes: Evidence from pakistan. *Social Science and Medicine*, 237:112453.

Hanna, R. and Oliva, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in mexico city. *Journal of Public Economics*, 122:68–79.

Harris, J. R. and Todaro, M. P. (1970). Migration, unemployment and development: A two-sector analysis. *The American Economic Review*, 60(1):126–142.

He, G., Liu, T., and Zhou, M. (2020). Straw burning, pm2.5, and death: Evidence from china. *Journal of Development Economics*, 145:102468.

Heckman, J. J. (2000). Policies to foster human capital. *Research in Economics*, 54(1):3–56.

Henlyey, J. and Willsher, K. (2015). Idps to start returning to their areas tomorrow. *Guardian*.

Herrnstadt, E., Heyes, A., Muehlegger, E., and Saberian, S. (2020). Air pollution and criminal activity: Microgeographic evidence from chicago. *Applied Economics*, Forthcoming.

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

Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151).

Ito, K. and Zhang, S. (2020). Willingness to pay for clean air: Evidence from air purifier markets in china. *Journal of Political Economy*, 128(5):1627–1672.

Jalil, X. (2016a). Lahore chokes as smog reaches new high. *Dawn*.

Jalil, X. (2016b). Why punjab's smog has aggravated this year? *Dawn*.

Jayachandran, S. (2006). Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy*, 114(3):538–575.

Jha, S. and Wilkinsan, S. (2012). Does combat experience foster organizational skill? evidence from ethnic cleansing during the partition of south asia. *The American Political Science Review*, 106(4):883–907.

Karahan, F. and Ozkan, S. (2013). On the persistence of income shocks over the life cycle: Evidence, theory, and implications. *Review of Economic Dynamics*, 16(3):452–476.

Kelly, M. (2000). Inequality and Crime. *The Review of Economics and Statistics*, 82(4):530–539.

Khan, R. S. (2015). Lahore smog: It's not a natural phenomenon. *Dawn*.

Khan, Y. (2017). *The Great Partition: The Making of India and Pakistan, New Edition*. Yale University Press.

Krueger, A. B. and Whitmore, D. M. (2001). The Effect of Attending a Small Class in the Early Grades on College-test Taking and Middle School Test Results: Evidence from Project Star. *The Economic Journal*, 111(468):1–28.

Lai, W., Li, S., Li, Y., and Tian, X. (2021). Air pollution and cognitive functions: Evidence from straw burning in china. *American Journal of Agricultural Economics*.

Lavy, V., Ebenstein, A., and Roth, S. (2014). The impact of short term exposure to ambient air pollution on cognitive performance and human capital formation. Working Paper 20648, National Bureau of Economic Research.

Leon, G. (2012). Civil conflict and human capital accumulation the long-term effects of political violence in perú. *The Journal of Human Resources*, 47:991–1022.

Levesque, S., Taetzsch, T., Lull, M. E., Kodavanti, U., Stadler, K., Wagner, A., Johnson, J. A., Duke, L., Kodavanti, P., Surace, M. J., and Block, M. L. (2011). Diesel exhaust activates and primes microglia: Air pollution, neuroinflammation, and regulation of dopaminergic neurotoxicity. *Environmental Health Perspectives*, 119(8):1149–1155.

Lin, M.-J. (2008). Does Unemployment Increase Crime? Evidence from U.S. Data 1974–2000. *The Journal of Human Resources*, 43(2):750–782.

Lochner, L. and Moretti, E. (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *American Economic Review*, 94(1):155–189.

Lu, J. G., Lee, J. J., Gino, F., and Galinsky, A. D. (2018). Polluted morality: Air pollution predicts criminal activity and unethical behavior. *Psychological Science*, 29(3):340–355. PMID: 29412050.

Maccini, S. and Yang, D. (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, 99(3):1006–26.

Mani, A., Mullainathan, S., Shafir, E., and Zhao, J. (2013). Poverty impedes cognitive function. *Science*, 341(6149):976–980.

Maree, A. (1999). Bank robbery in south africa: The crime and the criminal. *Security Journal*, 12:53–61.

McCollister, K. E., French, M. T., and Fang, H. (2010). The cost of crime to society: New crime-specific estimates for policy and program evaluation. *Drug and Alcohol Dependence*, 108(1):98–109.

McKenzie, D., Stillman, S., and Gibson, J. (2010). How Important is Selection? Experimental vs. Non-Experimental Measures of the Income Gains from Migration. *Journal of the European Economic Association*, 8(4):913–945.

Miguel, E. and Roland, G. (2011). The long-run impact of bombing vietnam. *Journal of Development Economics*, 96(1):1 – 15.

Miguel, E., Satyanath, S., and Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy*, 112(4):725–753.

Mincer, J. (1974). *Schooling, Experience, and Earnings*. New York: National Bureau of Economic Research.

Minnesota Population Center (2019). Integrated public use microdata series, international: Version 7.3 national census of pakistan 1973.

Moretti, E. and Neidell, M. (2011). Pollution, health, and avoidance behavior: Evidence from the ports of los angeles. *Journal of Human Resources*, 46(1):154–175.

Munshi, K. (2003). Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market*. *The Quarterly Journal of Economics*, 118(2):549–599.

Munshi, K. and Rosenzweig, M. (2016). Networks and misallocation: Insurance, migration, and the rural-urban wage gap. *American Economic Review*, 106(1):46–98.

Murphy, S. R., Schelegle, E. S., Miller, L. A., Hyde, D. M., and Van Winkle, L. S. (2013). Ozone Exposure Alters Serotonin and Serotonin Receptor Expression in the Developing Lung. *Toxicological Sciences*, 134(1):168–179.

Nafees, M. (2018). Annual security report -special edition. Technical report, Center for Research and Security Studies (CRSS).

Neta, C. (2018). Human cost of the post-9/11 wars: Lethality and the need for transparency. *Washington Institute International and Public Affairs*, pages 202–218.

Nunn, N. (2008). The Long-term Effects of Africa's Slave Trades*. *The Quarterly Journal of Economics*, 123(1):139–176.

of Finance, M. (2016). Pakistan economic survey. Technical report, Govt of Pakistan.

Ostro, B. D. (1994). *Estimating the health effects of air pollutants: a method with an application to Jakarta*, volume 1301. World Bank Publications.

Phillips, L., Votey, H. L., and Maxwell, D. (1972). Crime, youth, and the labor market. *Journal of Political Economy*, 80(3, Part 1):491–504.

Pratt, T. C. and Cullen, F. T. (2000). The empirical status of gottfredson and hirschi's general theory of crime: A meta-analysis. *Criminology*, 38(3):931–964.

Quah, E. and Boon, T. L. (2003). The economic cost of particulate air pollution on health in singapore. *Journal of Asian Economics*, 14(1):73–90.

Rambachan, A. and Roth, J. (2022). A more credible approach to parallel trends.

Rammal, H., Bouayed, J., Younos, C., and Soulimani, R. (2008). Evidence that oxidative stress is linked to anxiety-related behaviour in mice. *Brain, Behavior, and Immunity*, 22(8):1156 – 1159.

Rashid, A. (2012). *Pakistan on the Brink: The Future of Pakistan, Afghanistan and the West Ahmed Rashid*. Penguin.

Raza, M. and Abubakar, S. M. (2020). Smog gets in your eyes. *Dawn*.

Roth, J. (2019). Pre-test with caution: Event-study estimates after testing for parallel trends.

Rotton, J. (1983). Affective and cognitive consequences of malodorous pollution. *Basic and Applied Social Psychology*, 4(2):171–191.

Rotton, J., Barry, T., Frey, J., and Soler, E. (1978). Air pollution and interpersonal attraction1. *Journal of Applied Social Psychology*, 8(1):57–71.

Salmi, V. and Kivivuori, J. (2006). The association between social capital and juvenile crime: The role of individual and structural factors. *European Journal of Criminology*, 3(2):123–148.

Sanchez, M. and Wellschmied, F. (2020). Modeling life-cycle earnings risk with positive and negative shocks. *Review of Economic Dynamics*, 37:103–126.

Schilbach, F., Schofield, H., and Mullainathan, S. (2016). The psychological lives of the poor.

American Economic Review, 106(5):435–40.

Schlenker, W. and Walker, W. R. (2015). Airports, Air Pollution, and Contemporaneous Health. *The Review of Economic Studies*, 83(2):768–809.

Schultz, T. P. (2002). Wage gains associated with height as a form of health human capital. *The American Economic Review*, 92(2):349–353.

Sheldon, T. L. and Sankaran, C. (2017). The impact of indonesian forest fires on singaporean pollution and health. *American Economic Review*, 107(5):526–29.

Singhal, S. (2018). Early life shocks and mental health: The long-term effect of war in vietnam. *Journal of Development Economics*.

Stafford, T. M. (2015). Indoor air quality and academic performance. *Journal of Environmental Economics and Management*, 70:34–50.

Steckel, R. H. (1995). Stature and the standard of living. *Journal of Economic Literature*, 33(4):1903.

Strauss, J. and Thomas, D. (1998). Health, nutrition, and economic development. *Journal of Economic Literature*, 36(2):766–817.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199. Themed Issue: Treatment Effect 1.

Swee, E. L. (2017). Migrant networks and job search: Evidence from thailand. *Economic Development and Cultural Change*, 66(1):113–146.

Tan, T., Kudaisya, G., Gyanesh, K., and Dawsonera (2000). *The Aftermath of Partition in South Asia*. Routledge studies in the modern history of Asia. Routledge.

The World Bank (1973). World bank development indicators.

Thompson, J. (2014). A small measure of progress. *Foreign Policy*.

Todaro, M. P. (1986). Internal migration and urban employment: Comment. *The American Economic Review*, 76(3):566–569.

UNHCR (2020). Unhcr's refugee population statistics database. Revised: 12/08/2020. Accessed: 06/07/2021.

Vazsonyi, A. T., Pickering, L. E., Junger, M., and Hessing, D. (2001). An empirical test of a general theory of crime: A four-nation comparative study of self-control and the prediction of deviance.

Journal of Research in Crime and Delinquency, 38(2):91–131.

Yaduma, N., Kortelainen, M., and Wossink, A. (2013). Estimating mortality and economic costs of particulate air pollution in developing countries: The case of nigeria. *Environmental and Resource Economics*, 54(3):361–387.

Yang, D. (2008). International Migration, Remittances and Household Investment: Evidence from Philippine Migrants' Exchange Rate Shocks. *The Economic Journal*, 118(528):591–630.