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Does Violence in Non-War Zones Impact Labor Market Outcomes?

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Abstract

This paper analyzes a context where sustained violence happens in non-war zones. Specifically, this paper considers terrorist attacks in Pakistan and focuses on districts which were never an active war zone, but still suffered from intermittent terrorist attacks of varying intensity. We provide causal evidence on the effects of terrorist attacks on labor market outcomes. We find that the effect of terrorist attacks on incomes depends on the intensity of the attacks; it is also non-linear in nature as it gradually, but very slowly, shrinks to zero. After accounting for the intensity of the attacks, incomes reduce by about 15 percentage points on average due to terrorist attacks. The effects are more severe for highly skilled members of the labor force as well as for relatively inexperienced members. The two possible channels driving this impact are the changes in sectoral employment compositions and a reduction in the number of days worked. These findings add to the literature on conflict and violence by concluding that violence in non-war zones has important implications for labor market outcomes.

1 Introduction

There has been a great research interest in the socio-economic impacts of conflicts, violence and war. 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). Terrorism is one form of violence that has become commonplace in both active war zones as well as areas which are not part of a conflict. Little is known about how violence in the form of terrorist attacks in non-war zones impacts these socioeconomic outcomes.

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.

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 terrorist attacks in their non-war zones, such as Nigeria, Pakistan, Yemen etc., are more vulnerable to these attacks 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.

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.

I 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, a negative effect on labor market outcomes will imply that these non-war zones might need assistance in terms of mitigative and preventive policies, thus directly affecting humanitarian efforts and intervention programs.

Using an instrumental variable approach, we provide causal evidence that terrorist attacks in non-war zones negatively affects incomes. The effect is non-linear and varies by intensity of the attacks. Furthermore, individuals in districts with none to very few terrorist attacks do not experience a decrease in incomes, while individuals in districts with a higher number of attacks suffer a decrease in their incomes. These results can be extended to non-war zones in other areas of the world which suffer from sustained violence.

Terrorism -like any other form of conflict- can displace populations, disrupt schooling, destroy infrastructure and endanger civil liberties. However, the dynamics of terrorism in a non-war zone can be different and more complicated than a war or a civil conflict. Specifically, the military or the state is not actively involved in a war against an enemy or a non-state actor (GTD 2017); similarly, unlike a civil conflict, the terrorist or the insurgent group does not directly control some part of the territory. Second, the attacks are intermittent in nature and they can take place in the form of bombings, explosions, suicide explosions etc. However, 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).

Instead terrorists carry 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 scenario is comparable to incidences in other countries where certain terrorist groups 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 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 socio-economic 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 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 C. 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 three provinces. 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).

I use six rounds (2004-05, 2006-07, 2008-09, 2010-11, 2012-13, 2014-15) of repeated cross sectional individual data on labor market outcomes from Pakistan Social and Living Standards Measurement Survey (PSLM) and annual district 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 job market outcomes. Furthermore, 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 spatial and temporal spillovers and discuss potential mechanisms as well.

How terrorist attacks can affect labor incomes in on-war zones is still not well understood. Whereas there is research on the impact of civil wars on the long term macroeconomic costs of conflict (Abadie and Gardeazabal 2003), and the long term impact on labor market outcomes of those born during a conflict, by relying on critical programming theory, in Peru (Galdo 2013), it does not focus on non-war zones. This paper, on the other hand, focuses on the contemporaneous labor market outcomes at a microeconomic level due to violence in non-war zones.

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 zones 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.
1

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).

I 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 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 potential spillovers and heterogeneity. We then discuss the potential mechanisms leading to the change in individual incomes, followed by the conclusion section.

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

¹Grossman 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.

(FATA).² 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: FATA Region, and KPK Province

Figure 1 below 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.

Two important sources of data on terrorist attacks are the Global Terrorism

²Until 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.

Database (GTD) and Institute of Conflict Management's South Asian Terrorism Database (SATD).³ Both these data sources show that relative to other provinces, the KPK province suffered the worst due to terrorism.⁴ While FATA has been a constant conflict or war zone since the September 11 attacks (Rashid 2012), the KPK province has suffered the most after FATA while it wasn't a constant non-war zone.

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

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 Afghanistan 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).

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. KPK's share of population is 14.69% of Pakistan's population in the 2017 census and 17.58% in the 1997 census.⁵ Given the number of attacks in KPK, it is clear that KPK shared a disproportionate number of attacks relative to other three provinces.

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: majority of terrorist attacks in these provinces were undertaken by polit-

³GTD 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.

⁴The data on terrorist attacks is discussed in detail in the next section.

⁵Punjab 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%.

ical 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.

Figure 2: Terrorist Attacks in Each Province, 2004-2014. Source: GTD

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 there is another prominent increase again in 2012.

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 socioeconomic activities around the site of the attack.

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

Figure 3: Terrorist Attacks in Each Year in KPK Province. Source: GTD

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.

3 Data

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 to 2017. The GTD codebook defines a terrorist attack as “a threatened or actual use of illegal force 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).⁶

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

⁶Specific details about single event incidents, incidents with definition overlap etc. are also provided in the GTD.

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.

Table 1: Summary Statistics

(Individual and District Level Information Presented Separately)			
VARIABLES	(1) N	(2) mean	(3) sd
Individual 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 of Working Age Employed	394,519	0.292	0.455
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
Age Square	394,519	342.4	612.1
District Variables			
Annual District Attacks	138	11.32	30.90
Attacks Square	138	949.7	5,689
Annual District Fatalities	138	16.67	50.73
Annual District Injuries	138	25.41	78.89
Annual Avg. Attacks in Neighbor Districts	138	9.362	15.85
Distance (miles)	138	37.17	33.23
Avg. Distance for Neighbor Districts	138	-2.609	25.51
Predicted Annual Attacks	138	395.4	342.6
Distance * Predicted Annual Attacks	138	11.24	11,393
District Employment by Active Labor Force	138	93.97	7.054
District Percentage by Working Age Population	138	41.41	7.790

Given the above definition and criteria, all attacks carried out by terrorist orga-

nizations 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.

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, 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. The effect on farms, factories and manufacturing plants will depend on the number of annual attacks in a district. 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 second 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 (PSLM). 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.

Hence, the variation across districts in job market outcomes, intensity of attacks and other explanatory variables across districts of KPK province 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 considered pre-treatment while the remaining four rounds of data can be considered post-treatment.

The summary statistics for individual real income, number of attacks in each district in each year, distance and other time-varying control variables are provided in Table 1 below. The summary stats are for individuals in the working age. 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 percentage point change in income due to a certain number of terrorist attacks can be analyzed.

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 some variable inputs like fertilizer, raw material for firms etc. 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: $q_{it} = F(\alpha_{it}l_{it}, m_{it})$ 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.

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

$$\pi_{it} = p \cdot \alpha_{it} F(l_{it}, m_{it}) - w \cdot l_{it} - m_{it}. \quad (1)$$

Now, consider a terrorism shock S_{it} for firm i in year t , where $S_{it}(f_{it}, z_{it}) \in [0, 1]$. The shock depends on the intensity and the frequency of the terrorist attacks, respectively z_{it} and 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 $S_{it}(\cdot) = 1$, 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:

$$\pi_{it} = [1 - S_{it}(f_{it}, z_{it})] p \cdot [\alpha_{it} F(l_{it}, m_{it})] - w \cdot l_{it} - m_{it} \quad (2)$$

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

$$\frac{\partial \pi_{it}}{\partial l_{it}} = [1 - S_{it}(f_{it}, z_{it})] p \cdot [\alpha_{it} F'_l(l_{it}, m_{it})] - w = 0. \quad (3)$$

$$\implies l_{it}^* = l(p, w, S_{it}(z_{it}, f_{it}), \alpha_{it}(S_{it})). \quad (4)$$

Equations 3 and 4 above show that an individual 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 $\bar{L}$. 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 $\bar{L}$, the expression for aggregate labor demand can be obtained by summing the labor demand over all the firms:

$$\bar{L} = \sum_{i=1}^N [1 - S_{it}(f_{it}, z_{it})] p \cdot [\alpha_{it} F'_l(l_{it}, m_{it})] - w = 0. \quad (5)$$

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

$$w^* = \sum_{i=1}^N [1 - S_{it}(f_{it}, z_{it})] p \cdot [\alpha_{it} F'_l(l_{it}, m_{it})]. \quad (6)$$

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

$$\begin{aligned} \frac{\partial w}{\partial d_{it}} = & - \sum_{i=1}^N S'_{it}(d_{it}) p \cdot [\alpha_{it} F'_l(l_{it}, m_{it})] + \\ & \sum_{i=1}^N [1 - S_{it}(f_{it}, z_{it})] p \cdot [\alpha'_{it}(S'_{it}) F'_l(l_{it}, m_{it})] \end{aligned} \quad (7)$$

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, $-\sum_{i=1}^N S'_{it}(d_{it}) p \cdot [\alpha_{it} F'_l(l_{it}, m_{it})] < 0$. 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, $\frac{\partial \alpha_{it}}{\partial S_{it}} \cdot \frac{\partial S_{it}}{\partial d_{it}} < 0$ 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 $[1 - S_{it}(f_{it}, z_{it})] \geq 0$, the second expression in equation 7 on the right hand side $\sum_{i=1}^N [1 - S_{it}(f_{it}, z_{it})] p[\alpha'_t(S'_{it})F'_l(l_{it}, m_{it})] \leq 0$.

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 change in worker specific productivity levels due to the shock can affect income in two ways. First, it can be the case that the shock only affects aggregate worker productivity without affecting the production capacity of the economy, which translates into a decrease in wage. Second, the shock can affect both worker specific productivity levels and production capacity of the economy which also causes a decrease in wage.

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.

5 Methodology

My 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 also use an instrumental variable approach.

Consider the following main estimation equation:

$$\log(Y_{ijt}) = \beta_0 + \beta_1 Attacks_{jt} + \psi X_{ijt} + \phi_j + \gamma_t + \epsilon_{ijt}, \quad (8)$$

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 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.

As discussed earlier, the effect of attacks might be non-linear so the above equation

can be modified to:

$$\begin{aligned} \log(Y_{ijt}) = & \beta_0 + \beta_1 \text{Attacks}_{jt} + \beta_2 \text{Attacks}_{jt}^2 + \psi X_{ijt} \\ & + \phi_j + \gamma_t + \epsilon_{ijt}. \end{aligned} \quad (9)$$

The number of attacks in a district are correlated with the distance from the FATA region. 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.⁷ The longer the distance, the fewer the predicted number of attacks in that district. However, this distance would not vary overtime and does not allow me to fully exploit the temporal nature of the data.

I 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. The temporal variation in attacks in KPK can be predicted and interacted with the distance from FATA boundary to consider an instrument of the following form:

$$\text{Attacks}_{jt} = \alpha_1 \text{Distance}_j * \text{Predicted_Attacks}_t + \alpha_2 \text{Distance}_j + \alpha_3 \text{Predicted_Attacks}_t, \quad (10)$$

where Distance_j is the shortest possible distance from the center of district j to the FATA boundary; $\text{Predicted_Attacks}_t$ is the predicted attacks in KPK province for each of the six years for which income data is available; and $\text{Distance}_j * \text{Predicted_Attacks}_t$ is the interaction between both which serves as the main instrument.

Here, $\text{Predicted_Attacks}_t$ 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. Use of predicted instead of actual attacks in KPK ensures they are exogenous with respect to the annual attacks in each district (Duflo and Pande 2007).

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. However, the distance from FATA boundary does not vary over time and $\text{Predicted_Attacks}_t$ does not vary across districts. Instead, we estimate district by

⁷As we will show later, there are no trends in individual incomes as a function of distance before 2007.

year variation in terrorist attacks by including district and year fixed effects as shown below.

I include two interaction terms in my 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 invariant 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:

$$\begin{aligned} \log(Y_{ijt}) = & \beta_0 + \beta_1 Attacks_{jt} + \psi X_{ijt} + \tau Distance_j * Year_t \\ & + \kappa M_j * Predicted_Attacks_t + \phi_j + \gamma_t + \epsilon_{ijt}, \end{aligned} \quad (11)$$

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 8.

The corresponding first stage equation would be:

$$\begin{aligned} Attacks_{jt} = & \alpha_0 + \alpha_1 Distance_j * Predicted_Attacks_t + \theta X_{ijt} \\ & + \omega Distance_j * Year_t + \zeta M_j * Predicted_Attacks_t \\ & + \eta_j + \mu_t + \pi_{ijt}. \end{aligned} \quad (12)$$

Before we present the first stage results and discuss the validity and the exclusivity of the instrument, a couple of comments are in order. 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 23 only. 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, according to the wild cluster bootstrap method defined by Cameron et al. (2008).

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. This can be accounted for by normalizing the annual district attacks by district population or district area.

The first stage regression results are presented in Table 2. The first two column clusters the standard errors at district level. The first and second column normalize

Table 2: First Stage Results

	Annual District Attacks		
	(1)	(2)	(3)
	Normalized by: Population (Clustered by District)	Normalized by: Area (Clustered by District)	Normalized by: Population (Clustered by Year & District)
Distance * Prd. Attacks	-0.00493*** (0.00012)	-0.000628 (0.00039)	-0.00493*** (0.00005)
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	101,050	101,050	101,050
Number of districts	23	23	23
Number of Years	6	6	6
Craig-Donald Wald F stat	3,482	1,142	3,482
Kleibergen-Paap F stat	16.88	2.54	75.08
Avg. Attacks	11.32	11.32	11.32
Avg. Population(2017)	1,435,917		1,435,917
Avg. Area in Sq. km(2017)		2,907	
Avg. -Instrument	11.24	11.24	11.24

Standard errors are clustered at district level in column 1 & 2

Standard errors are clustered at both year and district level in column 3

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

the number of attacks by district population and district area respectively. Two statistics are presented regarding the first stage F-stat. Craig-Donald Wald F stat is the standard first stage F-stat reported with first stage results; it is well above 10 in both first and second columns.

However, when the standard errors are not assumed to be i.i.d. anymore, the Kleibergen-Paap F statistic is the valid test statistic for the first stage. Hence, we report the Kleibergen-Paap F stat for the first column. Column 1 shows that the instrument is strong enough and the weak instruments issue should not be a problem when annual district attacks are weighed by district population.

Column 3 normalizes the number of annual district attacks by its population and clusters standard errors by both year and district. Clustering by both year and district is necessary because it accounts for correlation in both components of the instrument: while the distance variable varies by district, the predicted number of attacks in KPK varies by year only.

Furthermore, the number of attacks in each district will be determined by the predicted number of attacks in the KPK province. For instance, if predicted attacks in KPK are zero for a particular year, then the actual attacks in each district in KPK are zero by construction. This implies the presence of system heteroskedasticity by construction.

As shown in column 3, 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 0.00493 points in column 3. Given the results in column 3 of Table 2, all the results presented include the number of attacks variable normalized by district population.

A key concern about the instrument is that it might be correlated with unobserved factors that affect labor market outcomes, leading to a violation of the exclusion restriction. One potential threat with regards to this concern could be differential pre-trends in income, in areas closer and further away from the FATA border. Incomes might be higher (lower) in areas closer (further) to the 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.

$$Y_{ijt} = \delta_0 + \delta_1 Distance_j + \delta_2 2006_t + \delta_3 Distance_j * 2006_t + \lambda X_{ijt} + e_{ijt} \quad (13)$$

If districts farther and closer to the FATA boundary (or their trends) do not differ in their labor market outcomes before the escalation of the terrorist attacks, we expect

Table 3: Checking for Pre-Trends in the Instrument

Dependent Variable: Log Real Monthly Income		
	(1)	(2)
	OLS	OLS
	Year $\leq$ 2006	Year $\leq$ 2006
Distance	-0.00043 (0.00096)	
Distance * 2006	-0.00064 (0.00070)	-0.00075 (0.00054)
District FE	No	Yes
Time FE	Yes	Yes
Observations	33,840	33,840
R-squared	0.202	0.217
Avg. Attacks	0.734	0.734
Avg. Log Income	8.088	8.088

Standard Errors are clustered at both year and district level

Robust standard errors in parentheses

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

δ_1 and δ_2 to be small and statistically insignificant. We present the results in Table 3. In column 2 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 both columns.

6 Results and Discussion

I start with running simple OLS and Fixed Effects regressions -without using the instrumental variable approach. Column 1 of Table 4 shows that contrary to the intuition, an OLS regression of individual incomes on the number of attacks in each year in each district increases individual incomes.

Table 4: OLS Regression

Dependent Variable: Log Real Monthly Income		
	(1)	(2)
	No Dist. Fixed Effects	Dist. Fixed Effects
Annual District Attacks	0.00286** (0.00136) [0.0601]	0.00006 (0.00089) [0.965]
District FE	No	Yes
Time FE	Yes	Yes
Observations	101,050	101,050
R-squared	0.342	0.355
Avg. Attacks	12.75	12.75
Avg. Population (2017)	1435917	1435917
Avg. Log Income	8.561	8.561

Standard Errors are clustered at both district and year level

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

However, the positive and statistically significant coefficient on the number of attacks goes away when the district fixed effects are included in column 2 of Table 4. This 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.

Table 5: IV Regression Main Estimation Equation

	Dependent Variable: Log Real Monthly Income		
	(1)	(2)	(3)
	IV	IV	IV
	(weighed by Intensity)		
Annual District Attacks	-0.00388 (0.00380) [0.506]	-0.01175 (0.03796) [0.702]	-0.01173*** (0.00435) [0.160]
Attacks Sq.		0.00002 (0.00007) [0.789]	0.00015* (0.00009) [0.318]
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
weighed by Fatalities	No	Yes	Yes
Observations	101,050	101,050	101,050
R-squared	0.346	0.324	0.341
Avg. Attacks	12.75	12.75	12.75
Avg. Population (2017)	1435917	1435917	1435917
Avg. Log Income	8.561	8.561	8.561

Standard errors clustered at district and year level; provided in round parentheses

Bootstrapped p-value provided in square parentheses

The attacks variable and its squared terms are normalized by population per 1 million

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

Therefore, in table 5, we present the main estimation equation results from the instrumental variable approach. Column 1 only has a linear term of the number of attacks in each district in each year. Columns 2 and 3 also include a squared term for the attacks; and column 3 presents results from a regression weighed by the annual fatalities in each district to account for the variance in the intensity of attacks.

The coefficient in columns 1 and 2 on annual district attacks is negative but it is not statistically different from zero. In column 3 of Table 5, a squared term in attacks is added. The coefficient is positive but it is also not statistically different from zero.

In column 3, we weight the regression by annual fatalities in each district. The annual district fatalities serve as a proxy for the intensity 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.

The linear term has a negative sign while the squared term has a positive sign implying that the effect of attacks on incomes decreases with an increase in the frequency of attacks. This result holds in almost all the robustness checks and sensitivity analysis that will be presented later. It seems to suggest that the initial attacks disrupt the incomes significantly but as the number of these attacks increase or as these terrorist attacks continue to take place overtime, the general economic environment might adjust to them.

Results in column 3 of Table 5 are statistically different from zero at 1% significance level from the district clustered standard errors, but the bootstrapped p-value is higher at 0.160. The results suggest that one additional attack reduces incomes, on average, by about 1.2 percentage points. Given the average number of annual district attacks, this suggests an average reduction in income by about 15 percentage points.

The squared term in attacks in column 3 is positive but it is small: the magnitude of both the terms suggests that the effect of an additional attack on incomes would be zero after about 79 annual attacks in a district. This implies more than one attack every five days on average would lead to no effect of terrorist attacks on individual incomes; such a high number of attacks would mean that a district's situation is more comparable to a war zone.

Second, as discussed in 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.⁸

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.

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.

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.

The general direction of these findings is consistent with 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 studies⁹ (Adelaja and George 2019a; George et al. 2020; Grossman et al. 2019). 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.

⁸I will discuss this in greater detail in the mechanisms section.

⁹The 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.

7 Robustness Checks

Before we move on to sensitivity analysis, it is important to consider and address the potential threats to identification. We consider two important threats to identification in the subsection below.

7.1 Potential Threat to Identification

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. For instance, the 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 results are presented in Table 6. The specification includes both a linear term in annual district attacks and a squared term in attacks.

The results show that terrorist attacks have no impact on employment, on average: as shown in table 6, the coefficient in both the regressions on the linear term in attacks is not only non-negative but more importantly, it is also statistically insignificant. The coefficient in columns 2, which is weighed by annual district fatalities, is extremely small. This suggests that the effect of terrorist attacks on the average probability of being employed is virtually zero.

Another potential threat to identification is out-migration. Although migration and permanent displacement is a more likely to take place in war-zones, a very high frequency of attacks can cause individuals to move out of a district. If this migration is mainly driven by highly educated workers, for instance, 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.

To check for this, we follow the strategy used by Maccini and Yang (2009): we regress the log of annual sample size in each district on the annual number of terrorist attacks in each district and the squared term of the attacks. The results are presented in Table 7 and they fail to reject the null hypothesis of no change in the sample size because of the escalation in terrorist attacks.

Table 6: Checking for Potential Self-Selection

	Dependent Variable: =1 if Employed	
	(1)	(2)
	IV	IV
		(weighed by Intensity)
Annual District Attacks	0.00708 (0.00943) [0.386]	-0.00030 (0.00021) [0.246]
Attacks Sq.	-0.00012 (0.00016) [0.378]	0.00000 (0.00000) [0.492]
District FE	Yes	Yes
Time FE	Yes	Yes
weighed by Fatalities	No	Yes
Observations	393,497	393,497
R-squared	0.259	0.405
Avg. Attacks	12.75	12.75
Avg. Population (2017)	1435917	1435917
Proportion Employed	0.292	0.292

Standard errors clustered at district and year level; provided in round parentheses

Bootstrapped p-value provided in square parentheses

The attacks variable and its squared terms are normalized at attacks per 1 million people

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

Table 7: Checking for Potential Out-Migration

Dependent Variable: Log of Annual District Sample Size		
	(1)	(2)
	IV	IV
Annual District Attacks	0.00582 (0.1219) [0.673]	-0.01208 (0.03271) [0.749]
Attacks Sq.	-0.00016 (0.00021) [0.499]	-0.00018 (0.00063) [0.770]
District FE	Yes	Yes
Time FE	Yes	Yes
weighed by Fatalities	No	Yes
Observations	138	138
R-squared	0.058	0.321
Avg. Attacks	11.32	11.32
Avg. Sample Size	4059	4059

Standard errors clustered at district and year level; provided in round parentheses

Bootstrapped p-value provided in square parentheses

The attacks variable and its squared terms are normalized at attacks per 1 million people

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

Table 8: Normalized Attacks -by District Area

Dependent Variable: Log Real Monthly Income	
	(2) IV
Attacks per 1,000 Square Km	-0.01102** (0.00478) [0.102]
Sq. of Attacks per 1,000 Square Km	0.00005** (0.00002) [0.103]
District FE	Yes
Time FE	Yes
weighed by Fatalities	Yes
Observations	101,050
R-squared	0.404
Avg. Area	2907
Avg. Attacks	8.695
Avg. Log Income	8.561

Standard errors clustered at district and year level; provided in round parentheses

Bootstrapped p-value provided in square parentheses

The attacks variable and its squared terms are normalized at attacks per 1,000 Sq. km.

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

7.2 Sensitivity Analysis

In this subsection, we consider different ways to check for the sensitivity of the results main discussed earlier. One concern could be that the impact of terrorist attacks differs by the size of the district.

To see how accounting for these can affect the results, we normalize the annual number of attacks in each district and the squared term in attacks by district area. We present the results in Table 8.

Column 1 of Table 8 presents the results with the attacks variable normalized by district area. Both the regressions are weighed by annual district fatalities. The results can be interpreted as the effect of an additional attack per 1,000 square kilometers. The coefficient on the linear term in attacks is statistically significant at 5% significance level.

The signs of both the coefficients and their interpretation remains the same: one additional terrorist attack reduces the incomes on average, but at a decreasing rate. However, the coefficients increase in size relative to the main estimation results in Table 5 for both the linear term in attacks and the squared term in attacks. These results suggest that the findings in the previous section are robust to various measurements of the attacks.

8 Heterogeneity and Potential Spillovers

In this section, we briefly discuss heterogeneity in the impact of terrorist attacks as well as the potential spatial spillovers in the effect of terrorist attacks.

The impact of any form of violence or conflict can vary by skill level. To see if that is actually the case, we split my sample into individuals with no education, individuals between 1 and 12 years of education and individuals with at least 12 years of education. The results are presented in Table 1 in the appendix.

The size of the coefficient on the linear term in attacks is the smallest for individuals with some but less than 12 years of education. The largest impact takes place for individuals with at least 12 years of education. The coefficient for those with at least 12 years of education is statistically different from zero; the coefficient for individuals with no education is just marginally insignificant at 10% significance level.

The results indicate that highly skilled members of the workforce are the most vulnerable to a decrease in their incomes followed by the least skilled individuals. It was noted in the data section that about 9.5% of the attacks were on the businesses where businesses were defined 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). Corporate offices, cooperatives, hospitals

etc. are likely to employ highly skilled members of the labor force which implies that these members of the labor force had more exposure to the terrorist attacks. This is corroborated by the fact that the most skilled members of the labor force faced the highest number of terrorist attacks, as shown in Table 1 in the appendix.

I also split the sample into individuals between 16 and 25 years of age, individuals between 25 and 35 years of age, individuals between 35 and 45 years of age and individuals above 45 years of age. The results are presented in Table 2 in the appendix. The largest impact takes place on the youngest age group and the smallest impact takes place for the oldest aged group. It is also only statistically significant for the youngest age group or the individuals in the 16-25 and 35-45 age groups. This suggests that more experienced individuals in the workforce are able to resist the shock from terrorist attacks while younger and relatively less experienced members of the workforce are more sensitive to a decrease in their incomes due to terrorist attacks.

The size of the coefficient reduces for the 25-35 age group but increases again for the 35-45 age group. The average number of annual district attacks faced by each age group is almost the same. Middle age members of the labor force, in the 25-35 age group, are more experienced than younger members of the workforce and are more productive than older members of the workforce (Mincer 1974), in the 35-45 age group. Hence, their earnings are more robust to shocks such as terrorist attacks in non-war zones.

Lastly, we explore the possibility that terrorist attacks might have spatial spillovers. Specifically, a very high number of terrorist attacks in one district can affect labor market outcomes in its neighboring districts. For this purpose, we include a term for the average number of annual attacks, in all the neighboring districts of each district. To construct an instrument for this variable, we calculate the mean distance from FATA boundary to the same neighboring districts of each district, and interact it with the annual predicted attacks for KPK province. we do not include a squared term of attacks in this specification.

The results are presented in column 1 of Table 3 in the appendix. There seem to be no spatial spillovers of the terrorist attacks, as the coefficient is not statistically different from zero. While the coefficient for annual district attacks is negative, the coefficient for average district attacks in neighboring districts does not have a negative sign as well. This is probably because of the intermittent nature of the attacks and the localized impact of the attacks in the sense that an attack only impacts a limited area.

9 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.

Table 9: Mechanisms: Employment Composition

	Dependent Variable: =1 if Employed		
	(1)	(2)	(3)
	LPM =1 if Agriculture	LPM =1 if Manufacturing	LPM =1 if Services
Annual District Attacks	0.00025 (0.00065) [0.751]	0.00133 (0.00108) [0.412]	-0.00205*** (0.00071) [0.036]
Attacks Sq.	-0.00001 (0.00000) [0.364]	-0.00000* (0.00000) [0.416]	0.00002*** (0.00000) [0.030]
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
weighed by Fatalities	Yes	Yes	Yes
Observations	119,117	119,117	119,117
R-squared	0.300	0.067	0.206
Avg. Attacks	7.064	15.69	16.32
Avg. Population (2017)	1435917	1435917	1435917
Proportion of Workers	0.323	0.198	0.450

Standard errors clustered at district and year level; provided in round parentheses

Bootstrapped p-value provided in square parentheses

The attacks variable and its squared terms are normalized at attacks per 1 million people

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

Two of the major pathways through which terrorist attacks can potentially affect incomes are labor demand and worker specific productivity factor. With regards to labor demand, it is difficult to ascertain the exact impact at the firm level because

of the lack of data. However, we provide some evidence using the employment compositions across economic sectors since information is available on the sector of the economy in which an individual was employed.

Table 9 presents results from linear probability models where dependent variable equals 1 if an individual is employed in agriculture, manufacturing or service sector respectively. We use the simple Linear Probability Model framework and include both the linear term in attacks and the squared term in attacks. Those individuals who were involved in unpaid work are also included; most of the workers involved in unpaid work belong to the agriculture sector.

Given the average number of attacks for workers in each sector of the economy, 7.4% of the service sector labor force moves out into agricultural and manufacturing sectors of the economy. The coefficient on the squared term for both sectors is positive but it is extremely small -it is zero up till 4th decimal point in all cases- suggesting that the changes in employment composition continue for a large number of attacks.

The labor force from the service sector tends to move to the agricultural and manufacturing sectors. The majority of the labor force moves into the manufacturing sector. As discussed before in the section on data, factories and manufacturing plants most likely did not face any direct terrorist attacks. This is true for farms as well; but while farms are an integral part of rural setting in any developing country, factories are usually located away from human residential settlements. This most likely explains the changes in employment composition in the favor of the manufacturing sector.

Two other economic reasons may help explain the disproportional shift towards manufacturing sector jobs. First, jobs in agricultural sector are more likely to not employ any skill used in the jobs in the service sector. Therefore, service sector workers might completely lack the skill set required to become a part of the agricultural labor force.

In addition, agricultural household models explain that household labor is usually also employed on farms in developing countries. Besides breaking down the separability between household consumption and production, it also drives down the marginal product of labor and hence, wages, in the agricultural sector.

Results from Table 9 suggest that service sector workers had to adjust to a different sectors of the economy. 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 the agricultural and manufacturing sectors. In a perfectly competitive labor market, this would imply lower wages for these workers in their new jobs compared to their previous jobs. This could be a major pathway to the decrease in incomes due to escalation in terrorist attacks.

The second notable pathway that can affect incomes is through reduction of work hours. Information is available on the number of days worked in a month for each worker. However, any changes in number of days worked can be due to an affect on

worker specific productivity factors, as well as due to changes in labor demand.

Table 10: Mechanisms

Dependent Variable: No. of Days Worked in a Month			
	(1)	(2)	(3)
	IV	IV	IV
	Agriculture	Manufacturing	Services
Annual District Attacks	1.20798 (3.87211) [0.699]	-0.03097 (0.04095) [0.5534]	-0.06649 (0.04680) [0.419]
Attacks Sq.	-0.02222 (0.07376) [0.698]	0.00008 (0.00082) [0.9415]	0.00072 (0.00090) [0.641]
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
weighed by Fatalities	Yes	Yes	Yes
Observations	30,668	22,980	50,963
R-squared	0.074	0.063	0.032
Avg. Attacks	7.064	15.69	16.32
Avg. Population (2017)	1435917	1435917	1435917
Avg. No. of Days Worked	24.80	23.60	27.26

Standard errors clustered at district and year level; provided in round parentheses

Bootstrapped p-value provided in square parentheses

The attacks variable and its squared terms are normalized at attacks per 1 million people

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

In Table 10, we present the results with the number of days worked in a month as the outcome of interest. The empirical specification used is the instrumental variable technique. Columns 1 to 3 present the results for agriculture, manufacturing and services sectors respectively. We include the individuals who were involved in unpaid work of any kind; most of these individuals were involved in unpaid farm work. However, we exclude those working individuals who only report the number of months worked in a year and do not report the number of days worked in a month.

Given the average number of attacks faced by workers in both sectors, the labor force in manufacturing sector experiences a reduction in the number of days worked

per month by about 2.06 percentage points on average, while the labor force in service sector experiences a reduction in the number of days worked per month by about 3.98 percentage points on average.

It is difficult to explain the reduction in number of days worked in the manufacturing sector, even though proportion of employed individuals in the manufacturing sector increased due to terrorist attacks. However, it might be the case that the recently employed workers in the manufacturing sector are only able to work part-time. Manufacturing sector workers may also require more commute to and from their workplace, which implies that their number of days worked per month are more likely to be affected by terrorist attacks. Farmers, on the other hand, usually employ labor from rural areas in developing countries, and usually from the same community; since terrorists targeted busy urban centers and markets where agricultural sector workers are less likely to be present.

Two plausible explanations may have led to this phenomenon. First, beyond a certain number of attacks, there is no or very little impact on the demand for labor: as the firms shut down or produce at their subsistence level, they have reached the minimum capacity of production. Second, workers also probably become immune to the sustained terrorist attacks overtime; this is suggested by the positive coefficient on the squared term in attacks. Unfortunately, lack of data on firm operations and inability to map each terrorist attack to individual workers means that empirical investigation of both explanations is not possible.

The coefficient on the linear term in attacks for agriculture sector is positive however as shown in column 2 of Table 10. The workers in agriculture sector faced only about 7.1 annual district attacks on average, as shown in Table 10, which is less than half of the average annual district attacks faced by the workers in manufacturing and service sectors. This statistic corroborates the earlier discussion that farms most likely did not face any direct terrorist attack.

Another possible explanation for the increase in number of days worked for agricultural sectors could be that since some members of the workforce have moved out of the agricultural sector, the remaining labor force had to work more number of days. Given that workers in agriculture faced less than half of the annual district attacks faced by the workers in manufacturing and services sectors, it might not be difficult to work more days.

It seems to be the case that terrorist attacks have a more severe impact on service sector workers. This is probably the case because service sector workers 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.

Since the data suggests that agricultural and manufacturing sector workers did not face terrorist attacks at their workplace, it seems that the workers who suffer are most likely those whose livelihoods are directly affected by terrorist attacks. 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.

10 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 and it is non-linear in nature. We find that violence in this context does not generate spatial spillovers due to the sporadic nature of the attacks and the limited area of impact of these attacks. The most likely pathways leading to the negative affect on individual incomes are the changes in employment compositions and reductions in work hours.

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. Violence in non-war zones is local in its impact relative to violence in war or conflict zones. Discussion in the previous suggestion suggests that, in this context, service sector workers are more vulnerable to being exposed to terrorist attacks which leads to service sector workers changing their sector of employment or reducing their work hours. The impact is relatively less severe for workers in other sectors that are less likely to be exposed directly to terrorist attacks.

In a similar way, policy makers can identify the most vulnerable group of the society 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. Thus, a smarter approach to relief efforts during or after the crisis could involve identifying the most vulnerable groups and prioritizing relief efforts towards them, instead of planning general relief efforts for the whole affected region.

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 is threatened the most due to these attacks. This evidence that workers whose livelihoods are directly affected by terrorist attacks are more likely to face stronger consequences implies that ensuring

the safety of their workplaces might play a critical role in mitigating the magnitude of the effect of terrorist attacks.

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 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 mitigative 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.

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Appendix

Table 1: Heterogeneity by Skill Level

Dependent Variable: Log Real Monthly Income			
	(1)	(2)	(3)
	IV	IV	IV
	No Educ	$0 < \text{Educ} \leq 12$	Educ > 12
Annual District Attacks	-0.01154 (0.00738) [0.355]	-0.00400 (0.00391) [0.499]	-0.02862*** (0.00894) [0.094]
Attacks Sq .	0.00019 (0.00016) [0.455]	0.00002 (0.00006) [0.810]	0.00040** (0.00018) [0.201]
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
weighed by Fatalities	Yes	Yes	Yes
Observations	39,903	45,783	15,364
R-squared	0.230	0.298	0.310
Avg. Attacks	11.93	13.20	14.22
Avg. Log Income	8.333	8.559	9.147

Standard errors clustered at district and year level; provided in round parentheses

Bootstrapped p-value provided in square parentheses

The attacks variable and its squared terms are normalized at attacks per 1 million people

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

Table 2: Heterogeneity by Age

Dependent Variable: Log Real Monthly Income				
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
	16 < Age ≤ 25	25 < Age ≤ 35	35 < Age ≤ 45	Age > 45
Annual District Attacks	-0.01593*** (0.00099) [0.0022]	-0.00622 (0.00833) [0.6118]	-0.01680** (0.00554) [0.137]	-0.00354 (0.00405) [0.4609]
Attacks Sq.	0.00016** (0.00005) [0.089]	0.00011 (0.00014) [0.5536]	0.00022 (0.00014) [0.3864]	0.00003 (0.00008) [0.6234]
District FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
weighed by Fatalities	Yes	Yes	Yes	Yes
Observations	24,734	29,033	22,057	27,337
R-squared	0.194	0.252	0.347	0.312
Avg. Attacks	13.06	13.14	13.28	13.29
Avg. Log Income	8.271	8.645	8.79	8.65

Standard errors clustered at district and year level; provided in round parentheses

Bootstrapped p-value provided in square parentheses

The attacks variable and its squared terms are normalized at attacks per 1 million people

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

Table 3: Spatial Spillovers

Dependent Variable: Log Real Monthly Income	
	(1)
	IV
	Spatial Spillovers
Annual District Attacks	-0.00981*** (0.00255) [0.0544]
Attacks Sq.	0.00007 (0.00006) [0.358]
Avg. Attacks in Neighboring Dist.	0.00236 (0.00362) [0.476]
District FE	Yes
Time FE	Yes
Observations	101,050
R-squared	0.344
Avg. Attacks in Neighboring Dist.	9.224
Avg. Attacks	12.75
Avg. Log Income	8.561

Standard errors are clustered at district level

Robust standard errors in parentheses

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