Ph.D. Thesis

Four Essays in Conflict Economics

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Declaration of Authorship

I, Luqman Saeed, hereby declare that the work presented in Chapters 1, 3, and 4 of this dissertation is entirely my own. Chapter 2 is based on the research conducted in collaboration with Professor Michael Spagat.

Chapter 4 resulted in the following publication

Saeed, Luqman (2018) " Education and Participation in Political Violence: A Look into Nonlinear Associational Patterns" *Peace Economics, Peace Science and Public Policy*, 24 (3): 1-11.

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Abstract

This dissertation is a collection of four essays that broadly fall in the field of conflict economics. In Chapter 1, I exploit a new database on humanitarian military interventions (HMIs) to study their impacts on conflict termination and escalation, human rights observance, and economic growth. I use heteroscedasticity -based instruments to tackle the endogeneity of HMIs. The results suggest that biased HMIs aggravate conflict intensity and lead to a large negative effect on economic growth. Neutral HMIs, in which interveners target all perpetrators of violence, are observed to positively impact conflict termination. Chapter 2 is co-authored with Professor Michael Spagat. In this chapter, we employ weather conditions and a dummy variable for drone base closure as instruments for drone strikes in an econometric model for suicide bombings in Pakistan. Reverse causality and the effects of unobserved common factors can cause the estimate for the drone strikes variable in an OLS model for suicide bombings to be biased. The results from IV regressions show that a drone strike is followed by at least 1 suicide bombing in the following month. In Chapter 3, I revisit the impact of military expenditures on economic growth. I employ arms imports during peace time and the number of neighboring states suffering interstate violence as instruments for military expenditures in an endogenous growth model. The results from the IV regressions indicate that a 1 percentage point increase in military expenditure/ GDP leads to around a 1.20 percentage points decrease in economic growth. Finally, in Chapter 4, I study the relationship between educational attainment and participation in political violence by exploiting a dataset on 200 militants of Pakistani origin and a representative sample of 13422 other Pakistanis. The empirical results indicate that a nonlinear model better fits the observed data on educational attainment and participation in political violence. The relationship is characterized by an inverted U shape form and the likelihood of engaging in political violence maximizes at about 12 years of schooling.

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Table of Contents

List of Tables

List of Figures

Introduction

This dissertation broadly falls in the field of conflict economics. It consists of four chapters and is concerned with investigating the impacts of humanitarian military interventions, drone strikes, and educational attainment on various manifestations of political violence. It also studies the impacts of humanitarian military interventions and military expenditures on economic growth.

Over the past few decades, the idea of military interventions on humanitarian grounds has received considerable attention in the international political arena as an effective and swift means of ending violent conflicts. However, it has also provoked discontent amongst some scholars who believe that such military interventions are counter-productive and escalate the conflict by encouraging parties that benefit from these interventions to continue fighting (Grigoryan, 2010; Kydd & Straus, 2013). I launch an investigation in Chapter 1 to examine that which of these views are supported by historical empirical evidence. In the first chapter, I exploit a new database on humanitarian military interventions (HMIs) to investigate their impacts on conflict termination and escalation, human rights observance, and economic performance. I estimate empirical models using panel data of 144 countries between 1960 and 2018 and to address the endogeneity problem, which might arise from reverse causality and omitted variables bias, I generate heteroscedasticity-based instruments and run IV regressions. I estimate intervention-level effects (controlling intervention-year with a dummy), size effects (number of troops deployed per million population), and long-run decaying effects over 5 years following the onset of intervention. The empirical results suggest that the biased HMIs escalate conflict and negatively affect economic growth. Against government, HMIs also adversely affect human rights observance. Neutral HMIs, in which interveners take military action against all parties, are observed to positively impact conflict termination.

The second chapter is co-authored with Professor Michael Spagat. Some analysts argue that US drone strikes targeting militants in the North Waziristan (NW) region of the erstwhile Federally Administered Tribal Areas (FATA) of Pakistan reduce militant activity. Others argue that these CIA-led strikes increase this activity. Cause and effect are difficult to disentangle because common underlying factors may drive both forms of violence. In Chapter 2 we use weather to identify a positive and large causal effect of drone strikes in NW on suicide attacks nationwide in Pakistan. Specifically, we use cloud cover and precipitation data for the NW, plus a dummy variable for a specific drone base closure, to instrument for drone strikes in the NW between July 2008 and the end of 2016 and identify a casual effect on suicide bombings in the whole country during this period. The idea is that drone strikes, but not suicide bombings, rely on good weather and appropriate air bases for their feasibility and effectiveness. We find that each drone strike causes, on average, at least 1 suicide bombing within the subsequent month, usually within a radius of 0 to 400 kilometers from the strike point. Strikes that eliminate militants' leadership provoke particularly large reactions. We characterize 27-33 percent of all suicide bombings from July 2008 through 2016 as reactions to drone strikes. These results are robust to a variety of alternative specifications and estimators.

Endogeneity problems have plagued efforts to estimate the impact of military expenditures on economic growth. In Chapter 3 I address this problem with two instruments for military expenditures: the value of arms imports during periods of peace and the number of neighboring states suffering interstate violence. The value of arms imports, while positively correlated with military expenditures, is unlikely to be determined by economic growth because of the time lag which exists, which in many cases runs into several years, between the placement of purchase orders for these arms and their delivery. The number of neighboring states suffering interstate violence represents regional "political uncertainty", which spurs military spending without at the same time manifesting the scale of domestic political violence which directly affects economic growth. Several diagnostic tests show that both these instruments are highly correlated with military expenditures and fulfill overidentification restrictions. The results from empirical analyses of panel data on 133 countries during the 1960-2012 period indicate that an increase in military expenditure/GDP of 1 percentage point reduces economic growth by 1.10 percentage points. This estimate of -1.10 is almost 3.91 times larger than the estimate obtained from the fixed-effect model which does not account for the endogeneity of military expenditures. These results are robust to the application of 2SLS, LIML, and GMM estimators.

Finally, in Chapter 4, I examine the impact of educational attainment on participation in political violence. The dearth of multivariate analysis on the relationship between these two variables is largely explained by the difficulties which are encountered in collecting information on the educational attributes of militants. Albeit the literature is limited, the findings suggest that educational attainment positively correlates with the likelihood of involvement in militancy (Krueger and Maleckova, 2003; Berrebi, 2007). I contribute to this literature by empirically examining whether the relationship between educational attainment and participation in political violence is characterized by non-linearities. I employ a self-created dataset on educational and other relevant attributes of 200 militants of Pakistani origin and a representative sample of 13422 Pakistanis. I obtained information on the educational and demographic attributes of militants of Pakistan origin by consulting the Counter-Terrorism Wing (CTW) of the Criminal Investigation Department (CID) of provincial police offices in Pakistan and newspaper archives. The results from weighted and unweighted probit estimations suggest that a non-linear model better fits the observed data on educational attainment and participation in political violence. The relationship assumes an inverted U shape form and the likelihood of participation in political violence maximizes at about 12 years of schooling. At no level of educational attainment, the likelihood of participation in political violence is observed to be negative. Hence, while educational attainment seems to be positively associated with involvement in political violence, there are considerable variations in the extent to which different levels of years of schooling affect political violence.

Chapter 1
Political and Economic Consequences of Humanitarian Military Interventions

1.1 Introduction

Are humanitarian military interventions (HMIs) effective in terminating violent conflicts, promoting human rights observance, and economic growth? Scholars and politicians who believe so argue that in some cases of violent conflicts, particularly those involving mass atrocities, HMIs are the only effective means of establishing peace. According to this pro-interventionist view, HMIs lower the intensity of conflicts which in turn lead to democratic and economic stabilities in the targeted countries (Smith, 1994; Power, 2007).[1] This view is challenged by the critics who contend that the pro-interventionists over-emphasize the normative appeal of HMIs without seriously evaluating their consequences (Mandelbaum, 1996; Reisman, 2004; Foley, 2010; Snow, 2015). HMIs, according to this critical view, lower the cost of violence for parties who benefit from these interventions and encourage them to continue fighting. In other words, HMIs are counterproductive and lead to conflict escalation (Grigoryan, 2010; Kydd & Straus, 2013).

In this paper, I exploit a new database on HMIs, developed by Gromes & Dembinski, (2019), and investigate their impact on conflict termination and escalation, human rights observance, and economic growth. I isolate the effects of biased and neutral HMIs and employ heteroscedasticity-based instruments, (Lewbel, 2012) to tackle the endogeneity of HMIs.

[1] Former British Prime Minister Tony Blair, a passionate advocate for humanitarian military interventions, said in his speech delivered at Sedgefield, the UK in 2004 "*The best defense of our security lies in the spread of our values*". Alluding to the sort of values which he thought must be promoted and which, in his opinion, should lead to political stability and economic prosperity, he further said "*citizens who are free, well-educated and prosperous tend to be responsible, to feel solidarity with a society in which they have a stake; so do nations that are free, democratic and benefiting from economic progress, tend to be stable and solid partners in the advance of humankind.*" Further articulating his defense of military interventions on humanitarian grounds "*And we do not accept in a community that others have a right to oppress and brutalize their people. We value the freedom and dignity of the human race and each individual in it.*" See full text of the speech at https://www.theguardian.com/politics/2004/mar/05/iraq.iraq

The empirical results suggest that biased HMIs in which intervener targets rebel forces and governments escalate conflict and have a large negative effect on economic growth. Neutral HMIs, in which intervener targets all perpetrators of violence, have a positive impact on conflict termination and no statistically significant negative impact on economic growth.

This paper is divided into the following sections. Section 1.2 presents descriptive statistics on HMIs which is followed by a brief discussion on theory and literature in section 1.3. Section 1.4 explains the methodological framework and data sources. Section 1.5 presents results followed by discussion and conclusion in sections 1.6 and 1.7.

1.2 Humanitarian Military Interventions since World-War II

Gromes & Dembinski (2019) define humanitarian military interventions (HMIs) as military interventions in which *threat or use of force is employed by a state or group of states for the purpose of saving strangers from violent emergencies.*[2] They record 41 cases of HMIs in the post-second world war period. In their database, the first recorded episode of HMI was the UN's intervention in D R Congo in 1960.[3] Interestingly only 6 HMIs were launched during the 1960-90 period where the ending year roughly coincides with the breakup of the Soviet Union.[4] In the following era, the number of HMIs exploded to 35.[5] In the majority of these HMIs, the principal interveners were either the UN, the NATO,

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[2] See details on definition, background and coding methodology at PRIF-data-set-HMI-codebook-v1-14.pdf (humanitarian-military-interventions.com)

[3] The United Nations intervened in the Congo's civil war which erupted between Moise Tshombe's rebel forces based in the region of Katanga and the government led by the then prime minister Patrice Lumumba.

[4] These interventions included India's intervention in the then East Pakistan in 1971, Arab League's intervention in Lebanon in 1976, Tanzania's intervention in Uganda in 1979, the USA's intervention in Lebanon in 1982 and India's intervention in Sri Lanka in 1987.

[5] An interesting political development of this era was the recognition of humanitarian intervention, under the title *Responsibility to Protect*, as a legitimate practice at the UN's World Summit in 2005. In the wake of controversies and divisions within the security council caused by the NATO's intervention in Kosovo, Kofi Anan, the then Secretory-General of the United Nations posed the question "if humanitarian intervention is, indeed, an unacceptable assault on sovereignty, how should we respond to a Rwanda, to a Srebrenica – to gross and systematic violations of human rights that affect every precept of our common humanity?" This triggered a response from the Government of Canada which set up an International Commission on Intervention and State Sovereignty to investigate political, moral, legal and operational challenges which underscore the idea of intervention. The commission finally formulated the idea of *Responsibility to Protect* according to which each state has a responsibility to protect its citizens from violence. If the state fails to do so, then in the words of commission's report *that responsibility must be borne by the broader community of states.* The commission's

or western countries, and the most frequently targeted countries were from Africa [see Table AP1-1 and Table AP1-2 in Appendix 1].

In 20 cases of HMIs, the interveners acted *neutrally* and deployed military force to stop violence from all the parties in the conflict [see Table 1.1].[6] Rebel forces were the main targets in 12 HMIs[7] whereas, in the remaining 9 cases of HMIs, the targets were the local governments [see Table 1.1].[8] Clearly, there are considerable variations in political positions assumed by the interveners in these HMIs. Next, I explore trends in key conflict variables in relation to biased and neutral HMIs.

Table 1.1 Types of Humanitarian Military Interventions (1960-2018)

Neutral	Against Rebels	Against Government
20	12	9

Data source: (Gromes & Dembinski, 2019)

Figure 1.1 illustrates trends in average intensity of conflict during HMIs years and over 7 years pre and post HMIs periods. Conflict intensity is measured on a three-point increasing scale of 0, 1, and 2 which represent less than 25, between 25-999 and 1000 & above battle-related deaths in a year's time, respectively.[9] Figure 1.1 shows that during most of the years in the pre-HMIs period average conflict intensities were higher than the global average, indicating the *excess intensity of conflict* in countries which experienced neutral and biased HMIs.[10] However, average conflict intensities elevated from these

report on Responsibility to Protect is available at http://responsibilitytoprotect.org/ICISS%20Report.pdf Since 2005, Responsibility to Protect has been invoked in 80 and 13 UN Security Council and General Assembly resolutions, respectively.

[6] Episodes of neutral HMIs include the Arab League's intervention in Lebanon in 1976, the UN's interventions in Bosnia and Herzegovina in 1994 and Sierra Leone in 1999, the European Union's intervention in DR Congo in 2003 and Chad in 2008.

[7] These include cases such as India's intervention in Sri Lanka in 1987, NATOs intervention in Bosnia and Herzegovina in 1994, UN intervention in Sierra Leone in 2000, African Union Intervention in Somalia in 2007 and US intervention in Iraq in 2014.

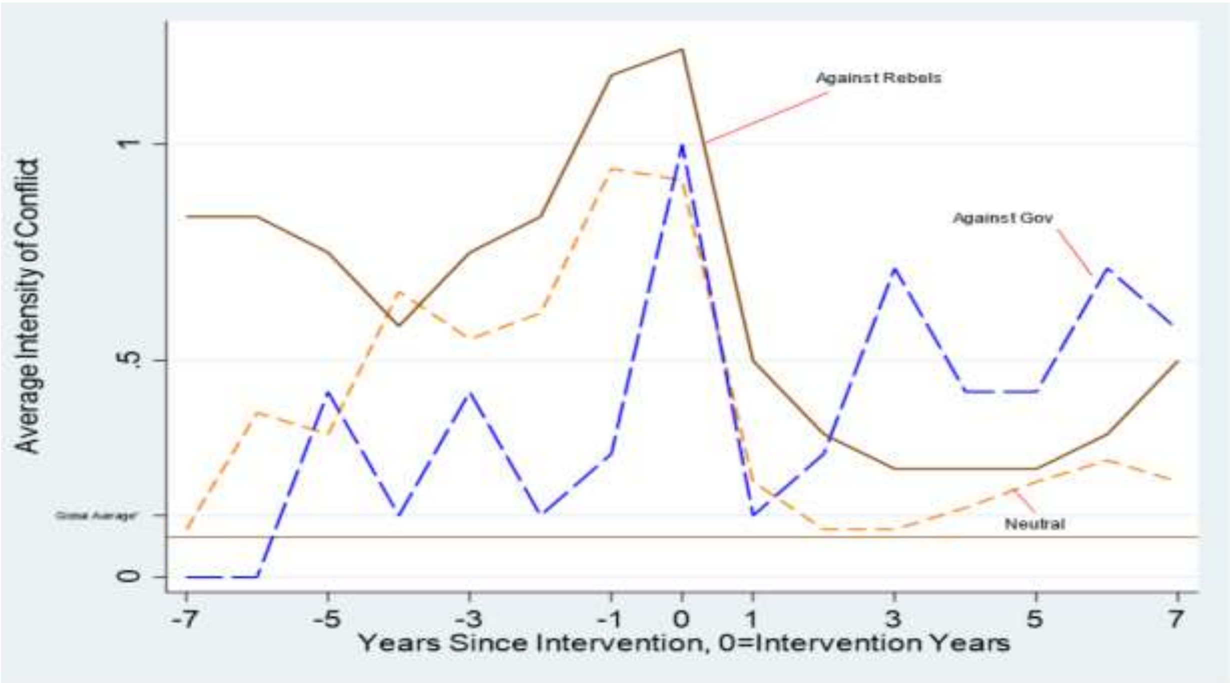
[8] Some prominent examples include India's intervention in the then East Pakistan in 1971, Tanzania's intervention in Uganda in 1979, Russia's intervention in Moldova in 1992, NATO's intervention in Kosovo in 1999, and the UN's intervention in Cote d'Ivoire in 2011.

[9] The data for conflict intensity is taken from the Uppsala Conflict Database Program.

[10] Average intensities of conflict were significantly higher in countries which eventually experienced against rebels and neutral interventions where on average violent emergencies had been going on for around 34-35 months before the start of interventions. On the other hand, conflicts were on average 17 months old before the start of against government HMIs. In fact, if we drop Tanzania's intervention in Uganda in 1979, then the average duration of conflict before intervention drops to 7.5 months in case of against government intervention.

levels when biased HMIs were ongoing, reflecting parallel worsening of conflict situations. This could happen for two reasons. First, it is possible that conflict escalation occurred independently of HMIs which were launched to contain the spiraling level of violence. Second, it is also possible that the elevations in conflict intensity were caused by the HMIs. To disentangle the cause and effect, I employ IV regression analysis in section 1.5.

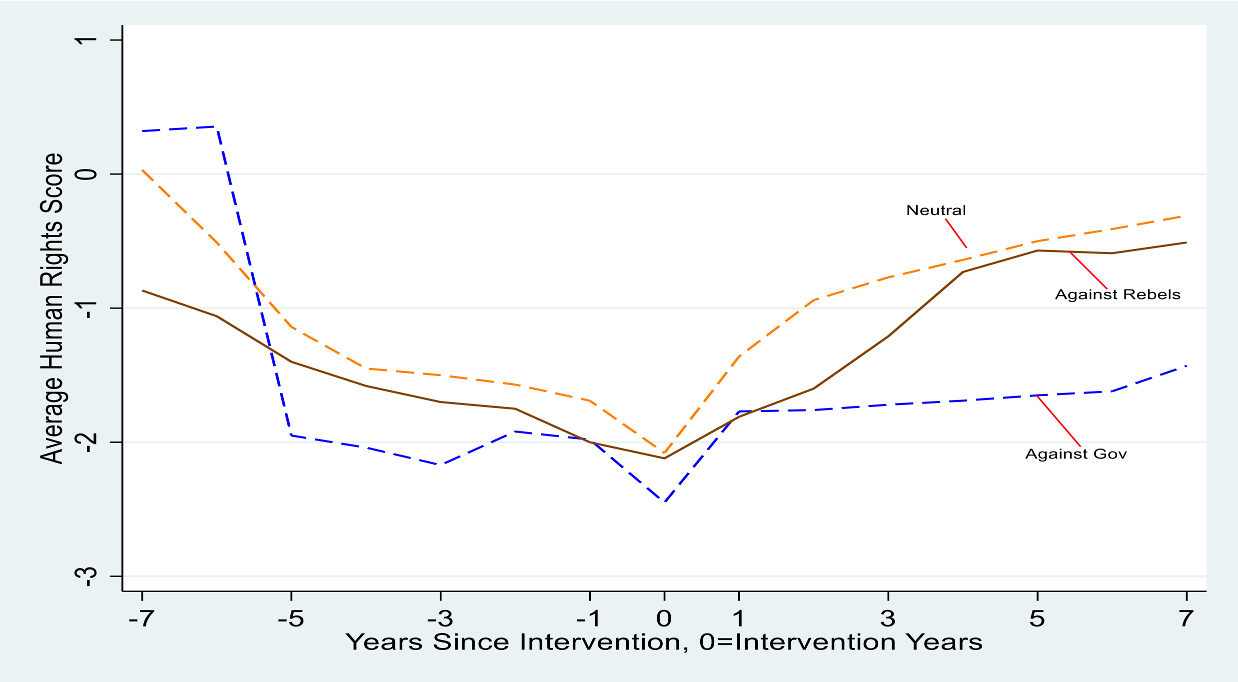
Figure 1.1 Average Intensity of Conflict and HMIs



On the other hand, in the case of countries that experienced neutral HMIs, there occurred a negative change in average intensity of conflict during HMIs years from the year immediately preceding the onset of these interventions. While these patterns are instructive about potential relationships, they alone do not furnish sufficient evidence to conclude about causal impact. However, at the minimum, it can be inferred that the objective of establishing political stability in the targeted countries was not fully achieved because these countries continued to experience *excess conflict*. For instance, in the post-biased HMIs period, while the average conflict intensities lowered from their intervention years level, they remained higher than the global average.

Figure 1.2 shows trends in human rights observance scores, before, during, and in post HMIs periods. This score reflects deviations from the global average set at 0 where the higher the score, the better is the human rights observance.[11] The average scores dipped to the lowest levels during the HMIs periods as compared with the levels during 7 years pre and post HMIs periods. The score for human rights observance measures repression exercised by the states. The sharpest fall in the score is observed in the case of against government HMIs, suggesting that the governments became more predatory once they came under assault by the foreign intervening powers.

Figure 1.2 Average Human Rights Score and HMIs



1.3 Theory, Hypotheses, and Brief Literature

While military interventions for humanitarian objectives have a long history[12], the debate about whether such interventions are legal and justified remains unresolved. The conflict between pro and anti-HMIs

[11] The data source for human rights observance score is Fariss, (2019)

[12] The term humanitarian intervention itself has modern origins but ideas and practices which it represents such as military actions to end atrocities, promote peace and democracy etc., were historically articulated on many occasions (Trim and Simms, 2011). So for instance, Virgil exhorted Romans to *crush the proud* and *impose peace* in foreign lands (Osborne, 2007: p 4). Thomas Aquinas (1125-1274) developed his thesis on just war in 13th century which had a significant impact on 16th century texts *Vindiciae contra tyrannos* and Theodore Beza's *The Right of Magistrates* which justified use of force to depose tyrants (Trim, 2011). While the treaty of Westphalia

perspectives is rooted in different philosophies and traditions of international law. Pro-HMIs school considers normative law and the legal rules/norms for international political order derived from it as morally superior to those inspired by the ideas of positive law. In opposition to the positivists, this school advocates against defining international laws based on the wills and actions of nation-states and contend that international law should be based on moral reasoning (Seybolt 2007: p 8). To put it simply, it attributes higher value to the rights of humanity than to the rights of the nation-states and argues that the respect for territorial sovereignty should not become an excuse for the international community's inaction against perpetrators of violence (Smith, 1994; Power, 2007; Walzer, 2006). Pro-interventionists further argues that as the sanctity and universality of human rights, at least in principle, have been universally acknowledged and endorsed in the international charters such as the UN's universal declaration of human rights, state sovereignty, interpreted as the state's right to non-interference in its domestic affairs, has become political anachronism (Smith 1994; Power 2002). Therefore, it is legitimate for the international community to intervene in foreign conflicts to stop atrocities if local governments are unable to protect their civilian populations or worse, are themselves perpetrators of violence.

To better understand how HMIs can help stop atrocities, assume that the payoffs from conflict depend upon the cost of violence and the probability distribution over three possible outcomes, i.e., victory, defeat, and settlement. HMIs can lead to conflict termination by increasing,

a) the cost of violence, and

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ended the war of religions and laid foundations for territorial sovereignty of States, this did not put an end to foreign military interventions. The catholic prince of the principality of Palatinate provoked a military response from Protestant counterparts when his political actions disturbed the confessional balance in his domain. English conservative and statesman Edmund Burke (1729-1797) led a vociferous campaign to depose *the most infernal tyranny* of the Jacobins in revolutionary France (Simms, 2011: p 103). John Stuart Mill (1806-1873), prolific English writer and liberal of 19th century wrote an influential essay titled *A Few Words on Non-Intervention* in 1859 in which he stressed that *whole doctrine of non-interference with foreign nations should be reconsidered* and that *there assuredly are cases in which it is allowable to go to war, without having been ourselves attacked, or threatened with attack*. This essay can be accessed at https://oll.libertyfund.org/title/mill-the-collected-works-of-john-stuart-mill-volume-xxi-essays-on-equality-law-and-education#lf0223-21_head_040. During the early 20th century, US Ambassador to the Ottoman Empire Henry Morgenthau Sr. worked tirelessly to provoke US action on Turks atrocities against the Armenian about which New York Times advocated to beat *Turkey to its knees* (Power,2002: p 9).

b) the probability of an unfavorable outcome.

This in turn lowers the expected payoff from engaging in violence and renders the use of force an unattractive strategy for pursuing political objectives (Kydd and Straus, 2013). In other words, HMIs that target perpetrators of violence can have a pacifying effect on conflict. They also compel autocratic regimes to respect the democratic and human rights of civilian populations (Smith, 1994; Brooks, 2012; Perriello, 2012). As the intensity of violence lowers, this, in turn, leads to a positive impact on economic performance as well.

This discussion leads to the formulation of the following set of hypotheses.

Hypothesis 1a- All else equal, humanitarian military interventions cause conflict termination.

Hypothesis 2a- All else equal, humanitarian military interventions cause conflict de-escalation.

Hypothesis 3a- All else equal, humanitarian military interventions improve human rights observance.

Hypothesis 4a- All else equal, humanitarian military interventions increase economic growth.

While the pro-interventionists emphasize the role of moral reasoning, the anti-interventionists argue in favor of political reasonings and wills of the nation-states as the principal force in the development of international law (Seybolt 2007: p 8). According to this perspective, the idea that all states have the right to non-intervention is the bedrock upon which the modern international political system is based. The stability of the system, whose evolutionary roots are traced back to the treaty of Westphalia (1648) which laid the foundation of the principle of non-intervention, will simply collapse if this principle of non-intervention is relaxed.

Some scholars have also emphasized practical challenges faced by intervening forces that render interventions ineffective and counter-productive. It is argued that military interventions inevitably lead to nationalist backlash because the human psyche is inherently disdainful of foreign military rule (Snow, 2015). For instance, Romans, despite bringing new technologies to the British island, could only maintain their rule by constantly deploying military force (Osborne, 2007, p. 109). In Iraq, the Shiite opposition to the US occupation developed despite that the Shiite community was the beneficiaries of the US decapitation of Saddam's regime.

Interveners also face insurmountable operational challenges which lead to the failure of interventions. Foreign conflicts are inherently complex and drive intervening forces into the asymmetric and unconventional styles of warfare for which they are mostly unprepared. The intervening forces have to confront military strategies such as hit-and-run tactics, suicide bombings, guerrilla ambushes, etc., in a political environment that eventually becomes hostile to the outsiders. These constraints are hard to overcome and despite bearing the enormous cost of intervention, interveners eventually withdraw without achieving any of their main objectives (Reisman, 2004; Snow, 2015). The US intervention in Afghanistan is one such case where even after 20 years of military action, the Taliban were able to regain power. In some cases, interveners themselves have been accused of questionable conduct such as supporting groups or regimes which are notoriously atrocious (Valentino, 2011).[13] Similar ideas are also articulated by some in the political Left who entirely dismiss the idea of HMIs as camouflage for imperialist expansion and which lead to humanitarian disasters. Lenin thought of notions such as *safeguarding peace, defense of democracy, etc.* as sugarcoating the real motives of seizing markets, resources, and political control (Trotsky, 1942).

Another important strand of anti-interventionist argument attacks pro-interventionists' implicit assumption of considering victims of violence as apolitical entities (Grigoryan, 2010). Starting with the assumption that all actors in a conflict are political actors who fight over political and economic resources, (Girgoryan, 2010; Kydd and Straus, 2013), it is argued that the biased HMIs augment the power of the supported group, reduce its cost of violence, and generates perverse incentives to continue fighting if the group is already militarily active or to launch a rebellion if it is inactive. As a result, biased HMIs lead to conflict escalation and the likelihood of negotiated solutions becomes remote.

[13] In a debate with Michael Chertoff, former US Secretary of Homeland Security and co-author of the Patriot Act, similar points were raised by Professor David N Gibbs from the University of Arizona. The debate can be accessed at https://www.youtube.com/watch?v=91WpiXu4oic

However, HMIs in which the intervener acts neutrally, raise the cost of violence for all parties and therefore can have a pacifying effect on conflict intensity.

Combining these different strands of anti-interventionist perspective, two sets of hypotheses can be formulated. In the first case, HMIs, in general, are considered to adversely affect conflict outcomes and by extension human rights observance, and economic growth as well. In the second case, biased HMIs are expected to have negative effects whereas neutral HMIs have positive effects on conflict outcomes.

I formulate both types of hypotheses and empirically test them in section V.

Hypothesis 1b- All else equal, humanitarian military interventions (biased and neutral) do not cause conflict termination.

Hypothesis 1.1b- All else equal neutral HMIs cause conflict termination.

Hypothesis 2b- All else equal, humanitarian military interventions (biased and neutral) cause conflict escalation.

Hypothesis 2.1b- All else equal neutral HMIs cause conflict de-escalation.

Hypothesis 3b- All else equal, humanitarian military interventions (biased and neutral) worsen human rights situations.

Hypothesis 3.1b- All else equal neutral HMIs improve human rights situations.

Hypothesis 4b- All else equal, humanitarian military interventions (biased and neutral) decrease economic growth.

Hypothesis 4.1b- All else equal neutral HMIs increase economic growth.

The majority of the empirical literature mainly covers the effects of military interventions in general and only considers HMIs as part of a wider analysis. While no empirical consensus underlines previous findings, the statistical methods employed in studies that suggest negative effects of military interventions- mostly biased interventions- are relatively more robust (Kim, 2012; Sawyer, Cunningham and Reed, 2015; Wood, Kathman and Gent, 2012; Pesken, 2012). If some of the recent findings from peacekeeping literature- which overlaps with neutral HMIs- is also factored in (Hultman, Jacob, & Shannon, 2013; Hegre, Hultman, & Nygård, 2018; Caruso, Khadka, Petrarca, & Ricciuti, 2016), there appear to be reasonable support for hypotheses 1.1b-4.1b that biased interventions escalate conflict and human rights violations whereas neutral HMIs lead to a positive effect on these variables and economic growth.

Nevertheless, to the best of my knowledge, none of the previous studies have addressed the issue of causality satisfactorily. As I explain in section 1.4.4, interventions and conflict variables are likely to be jointly affected by several other variables, many of which are difficult to be quantified and included in the model.

In a detailed study, Kim (2012) found that military interventions, including those motivated by humanitarian concerns, have no positive effect on reducing civil war duration. In particular, military interventions which are biased are observed to have a negative impact on conflict outcomes and civilian security. Like Kim (2012), Sawyer, Cunningham, and Reed (2015) found that biased interventions reduce the likelihood of civil war termination. Wood, Kathman, and Gent's (2012) findings suggested that biased interventions lead to an increase in atrocities against civilians. They argued that external military interventions, mostly by powerful states, lead to difficulties in resource extraction and fear of defections which motivate the targeted parties to increase the scale of violence against civilians. Pesken (2012) found that interventions that are supportive of governments increase the likelihood of extrajudicial killings and disappearance. While the focus of these studies was on military interventions involving non-humanitarian objectives, together their findings suggest that military interventions, and particularly those which are biased, have a deteriorating effect on conflict outcomes and human rights situations.

There is some evidence to the contrary as well. For instance, Krain (2005) found that neutral interventions are ineffective in stopping politicides and genocides. In a recent study, Conley and Hazlett (2020) surveyed 43 episodes of mass atrocities that resulted in killings of over 50, 000 people since the end of the second world war and found that 11 such episodes were ended by military interventions; all of which were biased. However, the findings are not based on multivariate analysis which enables partially out the effects of interventions while simultaneously controlling for other potential covariates.

Another relevant strand of literature is on the effects of peacekeeping missions. The United Nations enunciates three basic principles which underline peacekeeping missions which are 1) consent of the parties 2) neutrality and 3) use of force only in defense of forces deployed and the mandate.[14] Hence, the element of neutrality is common to both peacekeeping missions and neutral HMIs. The empirical evidence from large longitudinal studies seems to show that peacekeeping missions are effective in reducing the scale of violence. Hultman, Jacob, & Shannon (2013) found that increasing the number of UN military and police forces significantly reduces civilian fatalities in civil wars. In a recent study Bara & Hultman, (2020) extend the analysis to cover both UN and non-UN peacekeeping missions and show that both types of missions are effective in suppressing violence by the governments against civilians. Hegre, Hultman, & Nygård, (2018) examined all pathways- intensity, duration, recurrence, and diffusion- through which peacekeeping could affect conflict dynamics and found that had the UN invested $ 200 US billion in peacekeeping operations during 2001-13 period, there would have 150,000 fewer civilian fatalities.

The literature on the impact of military interventions on economic growth is very limited. To the best of my knowledge, Vishwasrao, Schneider, and Chiang (2019) is the only detailed study on the impact of foreign occupation on economic growth. These authors distinguish between the impacts of foreign occupations which are transformative and aim to develop institutions in occupied countries and those that are subdual which do not have any such objectives. In the empirical analysis of panel data on 214 countries covering the period of 1950-2013, they found transformative occupations to have a positive impact on economic growth both in the short and the long run. Pickering and Kisangani (2006) also found pro-government interventions to have a positive effect on growth.

On the other hand, the findings from peacekeeping literature seem to suggest positive effects of peacekeeping on economic outcomes. Beber, Gilligan, Guardado, & Karim, (2019) found a positive

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[14] For more see information on *what is peacekeeping* on the UN's peacekeeping webpage at https://peacekeeping.un.org/en/what-is-peacekeeping

impact of peacekeeping presence on local economies but the impact was not observed to last beyond the end of missions. Carnahan, And, & Durch, (2007) observed an upsurge in economic activity during the deployment of eight missions.[15] In a case study of South Sudan Caruso, Khadka, Petrarca, & Ricciuti, (2016) estimated that a 10 percent increase in the size of the deployment of UN troops lead to an increase of 600 tonnes in agricultural production.

1.4 Methodology

The empirical focus is on testing the impact of humanitarian military interventions (HMIs) on four main dependent variables which are 1) conflict termination, 2) conflict intensity, 3) human rights observance and 4) economic growth. This section illustrates measurement schemes and methodologies for estimating the models for each of these dependent variables.

1.4.1 Main Independent Variable: Humanitarian Military Interventions

Humanitarian military intervention (HMI) is the main explanatory variable of interest. The data for this variable is taken from Gromes & Dembinski (2019). To the best of my knowledge, Gromes & Dembinski's (2019) database is the first exclusive database on HMIs. Previous databases such as Pearson and Bauman (1993), Kisangani and Pickering (2008), and Sullivan and Koch (2009) provide information on both humanitarian and non-humanitarian military interventions but their criteria for identifying any military intervention as humanitarian is quite broad. For instance, Kisangani and Pickering (2008) categorize US relief efforts after the 2005 earthquake in Pakistan as a case of HMI. Gromes & Dembinksi (2019) is more relevant for the present inquiry because the focus here is on humanitarian interventions in which military force was deployed to address ongoing violent emergencies. Another advantage of the Gromes & Dembinksi (2019) database is that it is comparatively updated, and the current version ends in July 2019.[16] Their database covers a wide range of aspects of

[15] These included missions in Kosovo, Timor-Leste, Sierra Leone, Liberia, Coˆte d'Ivoire, Burundi, Democratic Republic of Congo, and Haiti.
[16] Pearson and Bauman's (1992) database ends in 1988 whereas Kisangani and Pickering (2008) cover the 1989-2005 period. Sullivan and Koch (2009) cover the 1945-2003 period.

HMIs, such as the identity and objectives of the intervener(s), the strength of military force deployed, etc., and also provides information on the aftermaths of intervention in the targeted country.[17]

I extracted data on the following three types of HMIs from the Gromes & Dembinski (2019) database

a) Neutral Intervention- where the intervener deploys military force to stop violence from all parties in the conflict.
b) Against Government- where the intervener acts to cause the defeat of the government of the targeted country.
c) Against Rebel- where the intervener targets rebel forces in the targeted country.

The rationale behind distinguishing between neutral and biased HMIs is based on the theory outlined in section 1.3 which postulates that biased HMIs can escalate conflict whereas neutral HMIs can have a pacifying effect on conflict. However, it also makes sense to separately control against government and against rebels HMIs. The military and logistical capabilities vary across the government and rebels groups-where rebels normally are the weaker party (Hultman, 2007)- which can shape the nature and strength of their responses to the outside military interventions. It is particularly important to distinguish between these two types of interventions in the economic output models. Governments' functions are not just limited to providing security but also, particularly in the developing world where HMIs take place, they also produce and consume a large portion of the economic output. Hence, it is plausible that the effects of HMIs that target government can be much stronger than the effect of against rebels HMIs. These interventions are measured in two forms. To capture the intervention-level effects, HMIs are measured in a binary form. In this case, the HMI variable assumes the value of 1 if the intervention is ongoing else 0. HMIs are also measured by the number of troops deployed. This variable captures the size-effect of intervention.

[17] Gromes and Dembinski (2019) database is open-source and can be accessed at https://www.humanitarian-military-interventions.com/downloads/

1.4.2 Main Dependent Variables

1.4.2.1 Conflict termination (CT)

The conflict termination (CT) variable is coded as 1 if conflict terminates in the following year. According to the Uppsala Conflict Data Program's (UCDP) criteria, a conflict starts if the number of battle-related deaths crosses a threshold of 25 in a year's time. This conflict is then declared terminated once after the onset, the criteria of over 25 battle-related deaths fail to be met. For instance, if a conflict is going on in-country A in year 1, and then if in year 2 the number of battle-related deaths falls below 25, CT is coded as 1 in year 1. The data source for conflict termination is the UCDP Conflict Termination Database Version 1.0 (Kreutz, 2010). I employ probit regression to estimate the parameters in the conflict termination model because this dependent variable is measured in a binary format.

1.4.2.2 Conflict Intensity

Conflict intensity (CI) is measured on a three-point ordinal scale of 0,1 and 2 where 0=less than 25 battle-related deaths, 1= 25-999 battle-related deaths, and, 2= 1000 and above battle-related deaths in a year's time.[18] The data for CI is also taken from the UCDP Conflict Termination Database Version 1.0 (Kreutz, 2010). Since CI is measured on an ordinal scale, therefore, I employ Ordered Probit Regression and Fixed Effect Regression to estimate parameters in the model.

1.4.2.3 Human Rights Observance

Human rights observance score is measured as deviation from the global average set at 0. The higher number reflects better human rights observance in a country. The data for this variable is taken from Fariss (2019) and in this case, I use Fixed Effect Regression to estimate the parameters. I also estimate Driscoll Kray standard errors to correct for autocorrelation, heteroscedasticity, and cross-sectional dependency (Hoechle, 2007).

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[18] The UCDP database only codes for cases when battle-related deaths are between 25-999 and 1000 & above. We code 0 for cases when the fatalities were below 25.

1.4.2.4 Economic Growth

Economic growth is measured as the annual change in GDP per capita and the source for this variable is world development indicators (WDI) of the world bank. To estimate the parameters in the economic growth model, I employ fixed effect regression and estimate Driscoll Kray standard errors (Hoechle, 2007).

1.4.3 Other Control Variables

Other explanatory variables include the onset of new conflict, log of the total and urban population, material capability, military expenditure as a percentage of GDP, ethnic fractionalization, and life expectancy.

The data for total and urban population, military expenditure, and life expectancy is taken from the world development indicators (WDI) database of the world bank. Material capability is a composite index of six variables which include military personnel, military expenditures, iron and steel production, primary energy consumption, total and urban population. The index is constructed by first dividing each state's share into these six components with the total of these components in the whole system. Then for each state, the average of all relative shares is computed which gives the index of material capability and which has a score between 0 and 1. The data for material capability is taken from the Correlates of War Project (Singer, Bremer, & Stuckey, 1972: Version 6.0). Ethnic fractionalization is measured as a probability of two randomly selected individuals from a country not being from the same ethnic group. The data for this variable is taken from Drazanova (2019). Table AP1-3 in Appendix 1 provides descriptive statistics for all these variables.

The total sample consists of 144 countries and covers the period 1960-2018.

1.4.4 Lewbel Method for Generating Instruments

The endogeneity of the main explanatory variable(s) is an important concern in multivariate analyses as it can cause estimates to be biased. I expect the humanitarian military intervention (HMI) variable to be endogenous for several reasons. First, conflict models can suffer from reverse causality since HMIs are launched in response to ongoing conflicts. Second, the models can also be affected by the omitted variable bias. For instance, the possible alliance between the intervener and any one of the parties in the conflict can trigger HMI, and while at the same time such an alliance, which might lead to covert military support, can influence the military capabilities of the supported party. The geography of a conflict-affected country can affect strategic calculations about whether to intervene or not in that country and at the same time might affect conflict dynamics as well. Information on these and all other similar variables are impossible to quantify and therefore they are not covered by the model.

The conventional method to address endogeneity is by using instruments that affect dependent variables only indirectly through the endogenous covariate. In the present context, it means that the valid instrument should be highly correlated with humanitarian military intervention variables (neutral, against government, and against rebels) but should have no direct effect on conflict dynamics. The number of cross-sections included in the present analysis are close to one hundred and fifty. While on the positive side, they are likely to enable drawing inferences about general patterns in how HMIs affect conflict dynamics but at the same time make it difficult to find an instrument which is valid for all cross-sections.

Lacking such an instrument, the alternative approach is to rely on the method which enables constructing instruments from within the data. For this purpose, I rely on the approach proposed in Lewbel (2012) which exploits heterogeneity in the errors of the endogenous covariate to build the instruments.

A good instrument should exhibit two properties. First, it should strongly correlate with the endogenous covariate. Second, it should be uncorrelated with the error term. The idea behind Lewbel's (2012) method is to bring together information from within the data which manifests these two qualities of a good instrument. The first component that Lewbel's (2012) method employs to construct instruments is the error term of the endogenous covariate. This error term strongly correlates with the endogenous covariate from which it is extracted. The more heteroscedastic this error term is, the more variation is obtained in this component which is used to develop the instrument.

To introduce the second quality, i.e. instrument is uncorrelated with the error, in the construction of the instrument, the Lewbel (2012) method relies on a set of exogenous control variables z in the model in the mean-centered form. These two components are then interacted to construct the instrument

$Instrumental\, Variable = (Z_j - \bar{Z_J}).\, \varepsilon_2$

Where ε_2 are the errors of endogenous covariate and Z is the set of exogenous variables in the model.

Consider the following set of equations,

$$Conflict_{it} = \beta_0 + \beta_1 HMI + X^{/}\beta_2 + \varepsilon_1$$

$$HMI_{it} = \beta_3 + \beta_4 Conflict_{it} + X^{/}\beta_5 + \varepsilon_2$$

where conflict and HMI are endogenous variables, X=vector of explanatory variables and $\varepsilon_1 \varepsilon_2$ = unobserved errors.

ε_2 is obtained by estimating equation 2. Since HMI is measured in a binary format, therefore, ε_2 is heteroscedastic by construction.

As stated above, this error term is then interacted with exogenous variables Z, where Z is equivalent to X or subset of X, in the mean-centered form to generate instruments. This requires fulfillment of the condition that the errors are independent of variables z. It is not possible to entirely validate this condition of *strict exogeneity* of Z, which is a population condition, and which in any case is not a necessary condition for the implementation of the Lewbel (2012) method. However, there are few variables in the model which can be assumed to be exogenous. These variables include lag values of total and urban population and ethnic fractionalization. Lag values of these demographic variables are not affected by conflict dynamics in year t. While anticipation of mass violence might affect population dislocations, such variations in demographic variables normally take place in response to active conflict. The data is processed yearly and radical population changes are unlikely to happen in anticipation of conflicts that occur with a lag of one year. It is also plausible to assume that no omitted variable would simultaneously affect current outcomes of conflict and past realizations of these demographic variables. In any case, the validity of instruments generated can be tested by using several diagnostic tests.

1.5 Results

1.5.1 Conflict Termination

The first set of results, reported in Table 1.2, are from Probit estimation of conflict termination models. I will mainly focus on interpreting results for key independent variables which are neutral and biased humanitarian military interventions (HMIs).[19] In model 1.2.1 the estimate for neutral HMIs is positive and statistically significant with a p-value of less than 1 percent. In model 1.2.2 regional dummies are included to control for some of the heterogeneity. The size of the estimate for neutral HMIs changes by a very small magnitude and the p-value is 1 percent. These results provide some preliminary evidence in support for hypothesis 1.1b that interventions in which the intervener acts neutrally against all parties in the conflict have a positive impact on conflict termination. There is no statistically significant evidence observed for against government and against rebels' HMIs to have any impact on conflict termination.

To determine whether these correlations reflect any underlying causal impact, I estimate model 1.2.3 by using instruments for both biased and neutral HMIs. The application of the standard IV-Probit estimator is inappropriate here as the endogenous covariates are not continuous.[20] However, the conditional mixed-process (CMP) framework as outlined in Roodman (2011) can be used for estimation of the system of equations in which HMIs are specified as endogenous variables. The advantage of using the CMP framework is that it allows estimation of two or more equations in which errors [seemingly unrelated system (SUR)] and the dependent variables are correlated (IV system). Unlike SUR, CMP allows estimation of a wide range of models, not just those with the continuous dependent variables, and the estimators can also vary in each equation.

[19] Full set of results for all covariates are reported in Table AP1-4 in the Appendix.
20 For more on appropriateness of IV-Probit estimator for models with different types of dependent variables see https://www.stata.com/manuals13/rivprobit.pdf

Table 1.2 Results for Conflict Termination Models

	Model 1.2.1	Model 1.2.2	Model 1.2.3	Model 1.2.4
	Intervention- Level Effect			Size Effect
Variables	**Probit**	**Probit**	**Conditional Mixed Process**	**Probit**
Neutral HMIs	0.757***	0.663***	0.673***	0.506**
	(0.00)	(0.01)	(0.00)	(0.02)
Against Government HMIs	0.236	0.242	0.416	0.097
	(0.83)	(0.82)	(0.71)	(0.20)
Against Rebels HMIs	0.413	0.387	0.182	0.122
	(0.31)	(0.34)	(0.62)	(0.30)
Other Controls	Yes	Yes	Yes	Yes
Regional Dummies	No	Yes	Yes	Yes
Wald- LR Statistic /Prob > chi2	248.41	254.73	711.00	254.87
	(0.00)	(0.00)	(0.00)	
Observations	5152	5152	5152	5152

*Parentheses contain p values. *** p< 0.01, **p<0.05. Robust clustered standard errors estimated in all models. Constant included in all models.*

A system of equation for conflict termination and HMIs variables is estimated where in the first stage biased and neutral HMIs are regressed on all exogenous variables and the instruments generated using the Lewbel (2012) method as outlined in section 1.4.4. In the second stage, the conflict termination model is estimated which includes predicted values from the first stage estimations. The findings from model 1.2.3 approximate those in models 1.2.1 and 1.2.2. The estimate for neutral HMIs is still positive and has a p-value of less than 1 percent whereas the estimates for biased HMIs are insignificant.

In Model 1.2.4, I control for the size of the HMIs by including the number of troops deployed by the intervening powers. It is plausible that the effects of interventions vary conditional upon the magnitude of force deployed. However, even after controlling for the size of HMIs, only neutral HMIs are observed to have a positive and statistically significant impact on conflict termination.

Together Models 1.2.1-1.2.4, in which I control for regional time-invariant effects and the endogeneity of HMIs, provide consistent and strong evidence in favor of neutral HMIs to have a conflict-pacifying effect. As an additional robustness check, I also estimate the models by restricting the sample to a set of countries that experienced at least 1 episode of conflict (more than 25 battle-related deaths in a calendar year) during the period 1960-2018. The results reported in Table AP1-4 in the Appendix show that the evidence for the positive effect of neutral HMIs on conflict termination is consistent with this variation in the sample.

1.5.2 Conflict Intensity

Table 1.3 presents findings from conflict intensity models. Models 1.3.1 and 1.3.2 are estimated using Ordered Probit Regression and Fixed Effects, respectively. In both models, no statistically significant effects of neutral and against government HMIs are observed on conflict escalation. On the other hand, the estimates for against rebels HMIs are positive and statistically significant with p values <= 1 percent which lends some support to hypothesis 2b. To account for endogeneity, Model 1.3.3 is estimated with a 2SLS estimator using instruments generated from the Lewbel (2012) method. The results are consistent with the pattern observed in Model 1.3.1-1.3.2 wherein against rebels HMIs are observed to intensify conflict. In model 1.3.4 I control for long-run decaying effects over 5 years period starting from the onset of intervention. Only against rebel HMIs are observed to have a statistically significant impact on conflict escalation in the long run.

Figure 1.3 presents average marginal effects of against rebels HMIs on conflict intensity based on the ordered probit estimation of Model 1.3.1. Countries that experience against rebels HMIs are on average 10 percent more likely to experience 25-1000 battle-related deaths (minor conflict) and around 8 percent more likely to experience 1000 and above battle-related deaths (war) as compared with the baseline of the group of countries which do not experience such HMIs.

In model 1.3.5 I partial out the size effect of HMIs on conflict intensity. The coefficient for against government HMIs, which is mostly insignificant in intervention-level models, becomes significant. This suggests that the impact of against government HMIs on conflict intensity, to an extent, depends upon the magnitude of ground forces deployed by the intervener(s). The deployment of ground forces is likely to provoke clashes with the local targeted governments causing a high number of battle-related deaths. The evidence for the effect of against rebel HMIs, as measured by the size, on conflict intensity is consistent and strong.[21]

Table 1.3 Results for Conflict Escalation Models

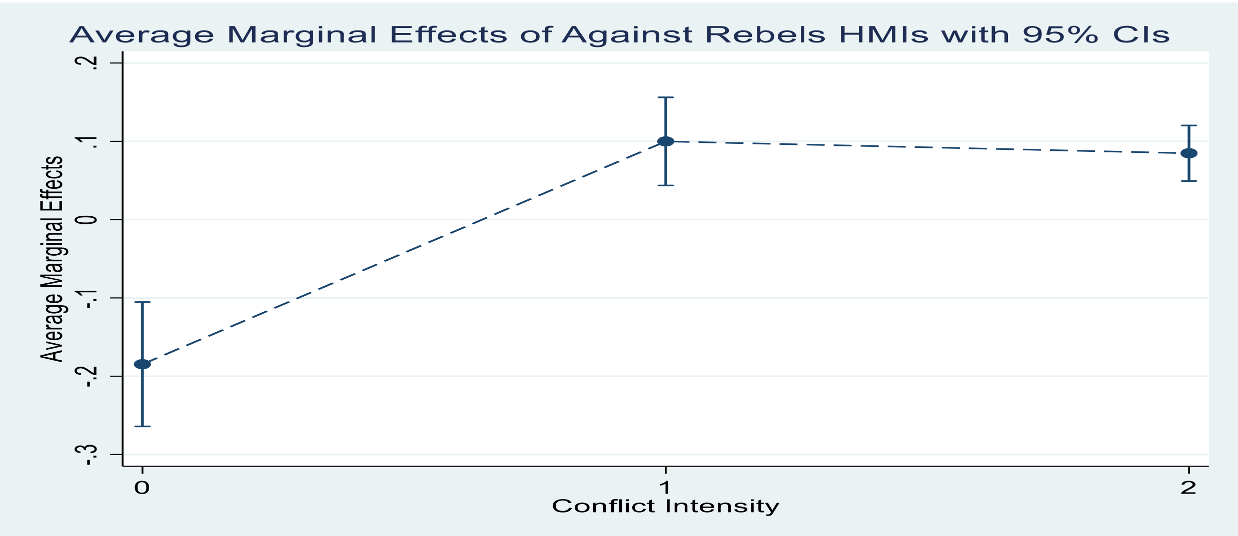
	Model 1.3.1	**Model 1.3.2**	**Model 1.3.3**	**Model 1.3.4**	**Model 1.3.5**
		Intervention-Level Effect			**Size Effect**
Variables	**Ordered Probit**	**Fixed Effect**	**2SLS**	**Ordered Probit**	**Ordered Probit**
Neutral HMIs	-0.018 (0.92)	-0.001 (0.99)	-0.003 (0.96)		-0.001 (0.33)
Against Government HMIs	1.07 (0.16)	0.455 (0.20)	0.423 (0.24)		0.002*** (0.00)
Against Rebels HMIs	1.38*** (0.00)	0.514** (0.01)	0.539*** (0.00)		0.002*** (0.00)
Neutral HMIs Decay Effect				-0.135 (0.79)	
Against Government HMIs Decay Effect				0.113 (0.68)	
Against Rebel HMIs Decay Effect				1.18*** (0.0))	
Other Controls	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes			Yes	Yes
Wald- LR Statistic /Prob > chi2	742.01 (0.00)			709.02 (0.00)	624.73 (0.00)
F Statistic Prob> F		186.55	70.32		

[21] These results are also consistent in the models estimated by restricting the sample to a set of conflict-affected countries.

		(0.00)	(0.00)		
Kleibergen-Paap rk Wald F statistic			164.19		
Hansen J Statistics p-value Ho: Instruments uncorrelated with errors			0.10		
Observations	4787	4796	4779	4787	4787

*Parentheses contain p values. *** p< 0.01, ** p<0.05. Robust clustered standard errors estimated in all models. Constant included in all models.*

Figure 1.3 Average Marginal Effects of Against Rebels HMIs



Solid lines show confidence intervals

1.5.3 Human Rights Observance

The results in Table 1.4 suggest that only against government HMIs have a negative and statistically significant impact on human rights observance. This effect is consistent in both intervention level (model 1.4.1-1.4.2) and size effect (model 1.4.3) models. The estimates for against rebels and neutral HMIs are insignificant. Note that the human rights score reflects state-led oppression. It makes sense that once local governments are attacked by the outside intervening powers, they become more predatory towards their opponents. However, no statistically significant long-run effects of against government HMIs are observed.

Table 1.4 Results for Human Rights Protection Models

	Model 1.4.1	Model 1.4.2	Model 1.4.3
	Intervention- Level Effect		**Size Effect**
Variables	**Fixed Effects**	**2SLS**	**Fixed Effects**
Neutral HMIs	0.013	0.058	0.013
	(0.73)	(0.23)	(0.71)
Against Government HMIs	-0.177*	-0.229***	-0.031***
	(0.07)	(0.00)	(0.00)
Against Rebels HMIs	-0.061	-0.030	-0.011
	(0.33)	(0.60)	(0.47)
Other Controls	Yes	Yes	Yes
F Statistic Prob > F	3170.59	2569.94	3080.17
	(0.00)	(0.00)	(0.00)
Weak Identification Test (Kleibergen-Paap rk Wald F statistic)		88.24	
Hansen J Statistic p-value Ho: Instruments are uncorrelated with errors		0.22	
Observations	4875	4410	4875

*Parentheses contain p values. *** p< 0.01, * p<0.10. Robust clustered standard errors estimated in all models. Constant included in all models.*

1.5.4 Economic Output

Table 1.5 reports results from economic growth models. In these models, along with control variables mentioned in section 1.4.3, I also include several time dummies which control for the Iran-Iraq war (1980-1988), gulf war (1990-1991), the financial crisis of 2008-09, post-cold war period when several soviet influenced economies were liberalized and economic recession of 1974-75 following the oil price shock of 1973. Unsurprisingly, biased interventions which tend to escalate the conflict- as suggested by findings in Table 1.5 – are also observed to have a strong negative impact on economic growth. The estimates suggest that countries which experience against government and against rebels HMIs experience around a 7-8 percent reduction in economic growth rate as compared with the baseline group of countries that experience no such interventions. Haiti's GDP per capita growth rate in 1994- when the US intervened- dropped to negative 13.59. Libyan GDP per capita contracted by an astronomical 62 percent in 2011- the year NATO intervened in the Libyan conflict. Of course, not all this reduction in growth rate can be attributed to biased HMIs which these countries experienced. Nevertheless, the estimates are quite high in magnitude and the effects are significant.

The negative effects of biased HMIs on economic growth persist even in the long run (Model 1.5.3).In the size effect model, the estimate for against rebels HMIs loses statistical significance while for against government HMIs it remains significant.

Table 1.5 Results for Economic Growth Models

	Model 1.5.1	**Model 1.5.2**	**Model 1.5.3**	**Model 1.5.4**
	Intervention- Level Effect			**Size Effect**
Variables	**Fixed Effects**	**2SLS**	**Fixed Effects**	**Fixed Effects**
Neutral HMIs	-0.892 (0.71)	-1.67 (0.64)		-0.020 (0.46)
Against Government HMIs	-7.12*** (0.00)	-6.43*** (0.00)		-0.01*** (0.00)
Against Rebels HMIs	-8.03** (0.01)	-7.85* (0.05)		-0.019 (0.14)
Neutral HMIs Decay			-4.42 (0.35)	
Against Government HMIs Decay			-7.39*** (0.00)	
Against Rebel HMIs Decay			-6.58*** (0.00)	

Other Controls	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
F Statistic/Wald chi2	56.67 (0.00)	14.53 (0.00)	18.29 (0.00)	44.81 (0.00)
Within R-square/Centered R square	0.12	0.11	0.11	0.11
Weak Identification Test (Kleibergen-Paap rk Wald F statistic)		84.93		
Hansen J Statistic p-value Ho: Instruments are uncorrelated with errors		0.42		
Observations	4492	4471	4373	4492

*Parentheses contain p values. *** p< 0.01, * p<0.10. Robust clustered standard errors estimated in all models. Constant included in all models. Time dummies control for Iran-Iraq war (1980-1988), Gulf War (1990-91), post-cold war period, the financial crisis of 2008-09, and economic recession of 1974-75.*

1.6 Discussion

Various scholars and politicians have lent support to the idea of humanitarian military intervention (HMIs) as an effective means for stopping atrocities and promoting political and economic stability. Indeed, the horrors of mass violence in countries such as Rwanda and Bosnia which *shocked the conscience of mankind* suggest a strong case for such interventions. This study does not attempt to evaluate the principles upon which the idea of HMIs is based. Rather the analyses are restricted to the examination of historical data to evaluate the political and economic effects of HMIs. The empirical results reported in the previous section seem to challenge the optimism that many have expressed about the role of HMIs as a stabilizing political practice. HMIs that are biased against government and rebels are observed to increase conflict intensity. Several case studies indicate that this happens by encouraging the parties which benefit from these interventions to continue fighting.

A relevant and illustrative case in this regard is that of African Union intervention in Somalia in 2007. The African Union Mission in Somalia (AMISOM) was established in 2007 to provide security to civilians and government officials against attacks from Al-Shabaab.[22] The intensity of violence increased after the intervention. While one contributing factor was the aggressiveness of Al-Shabaab but another important factor was AMISOM partisanship. Human Rights Watch in its report described AMISOM action as *turning a blind eye to their allies‘ abuses on the ground* (Human Right Watch, 2010; 5). The intensity of violence which according to the UCDP measure was 1 in 2006, increased to 2 and stayed at that level until 2012.

Another such case was that of the Force Intervention Brigade (FIB) of United Nations Mission in the Democratic Republic of Congo which was established in 2013 to counter four armed groups which included the Front for the Patriotic Resistance in Ituri (FRPI), Lord's Resistance Army (LRA), Allied Democratic Forces (ADF) and the Democratic Forces for the Liberation of Rwanda (FDLR)) (Day, 2017). The biased nature of this intervention was evident from the fact that out of a total of 70 armed groups in DR Congo, the FIB only confronted the above four militias. The other militant groups, therefore, remained undeterred. The mission, worked in collaboration with the Congolese army which was accused in the United Nations' confidential report *as a party to numerous violations* and *a significant force of sexual violence, notably against the minors.*[23] Further accusations were made in the UN's 2017 report which said that the Congolese army was responsible for 64 percent of documented violations of human rights, including extrajudicial killings of at least 480 civilians in 2016 (United Nations Security Council, 2017: p 7). It appears that the intervention in support of the Congolese army which has a dismal human rights record contributed to inan creasing in the scale of its atrocities against civilians and its opponents. DR Congo was already embroiled in a bloody conflict before the intervention was launched and had a conflict intensity level of 1 in 2012. However, after the intervention, this level increased to 2 in 2013. Hence, it seems that in both cases of Congo and Somalia, biased interventions ended up generating incentives for the supported parties to increase the level of atrocities.

[22] AMISOM is composed of troops from African countries such as Kenya, Uganda, Burundi, Djibouti, and Ethiopia.
[23] Cited in Charbonneau & Nichols, (2013). Report available at https://uk.reuters.com/article/congo-demomcratic-un-idINDEE9BG01A20131217

The results lend support to the effectiveness of the neutral intervention, where the intervener acts indiscriminately, in conflict termination. The United Nations and African Union intervention in the Central African Republic's civil war was successful in reducing atrocities against civilians at least in the first two years.[24] The United Nations Multidimensional Integrated Stabilization Mission in the Central African Republic (MINUSCA) collaborated with the French forces to protect the civilian population from militias.[25] The conflict intensity which had been at the level of 1 since 2009 fell to 0 in 2014 after the launch of intervention in 2013.[26] The Arab League intervention during the early stages of the Lebanese civil war in 1976 also demonstrated neutrality towards implementing peace. The intervention did lead to a reduction in the level of violence in its immediate aftermaths (Pogany, 1987). The conflict intensity which was at the level of 2 during the time of intervention in 1976 fell to 0 and remained at that level until the start of the second phase of the civil war in 1982. These cases support the empirical findings of this study that neutral interventions have positive effects on conflict termination whereas those which are biased lead to conflict escalation.

The result that neutral HMIs do not lead to any significant impact on economic output seems plausible given that these HMIs have a positive impact on conflict termination. Biased HMIs, on the other, hand are observed to have significant negative impacts on economic growth with the largest drop predicted in case of against government HMIs. Government is one of the most important actors in the economy responsible for enforcing contracts and providing supporting infrastructure, such as various public services, for economic activity. Military intervention against the government is likely to generate a climate of uncertainty and reduce producers' and consumers' confidence leading to a sizeable decrease in economic output (Pickering & Kisangani, 2006). The GDP per capita of Haiti fell by around 13 percent in 1994 after the United States launched a military intervention to topple the military regime and by 62 percent in Libya during the 2011 revolution and NATO intervention. These total reductions

[24] The conflict in CAR was between Muslim rebels and Christian militias "anti-balaka" which erupted into civil war in 2012.
[25] Howard (2019) reports that the spirit of the French mission could be articulated as "tu bouges t'es mort" that is, if you attack civilians, you are dead.
[26] The scale of violence, however, increased after the departure of French forces.

in output cannot be attributed entirely to military interventions. Nevertheless, the size of estimated coefficients, which is around -8 percent, indicates that the negative impact of biased HMIs is significant.

1.7 Conclusion

In this paper, I examine the impacts of humanitarian military interventions (HMIs) on conflict termination and escalation, human rights observance, and economic growth in the targeted countries. I exploit a new database on HMIs developed by Gromes and Dembinski (2019) and address the endogeneity of HMIs by using heteroscedasticity-based instruments. The empirical results indicate that the biased HMIs escalate conflict and have a large negative effect on economic growth. In addition to escalating conflict, against government, HMIs also adversely affect human rights observance. On the other hand, neutral HMIs in which intervener targets all perpetrators of violence are observed to have a positive effect on conflict termination.

Appendix 1

Table AP1-1 Selected Principal Interveners

Principal Intervener	Number of Interventions
United Nations	14
United States	6
NATO	4
France	2
Australia	2
European Union	2
India	2
African Union	1
Arab League	1

Table AP1-2 Selected Intervened Countries

Intervened Countries	Number of Interventions
Democratic Republic of Congo/Congo	4
Sierra Leone	3
Iraq	3
Lebanon	3
Somalia	2
Haiti	2

Bosnia and Herzegovina	2
Cote d’Ivoire	2

Table AP1-3 Descriptive Statistics

Variables	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Against Government HMI	11,001	0.00118	0.03436	0	1
Against Rebel Intervention	11,001	0.00509	0.07117	0	1
Neutral HMIs	11,001	0.00664	0.08119	0	1
Conflict Termination	11,001	0.03272	0.17792	0	1
Conflict Intensity	11,001	0.17262	0.47378	0	2
Conflict Onset	8,627	0.02202	0.14677	0	1
GDP Per Capita (2010 prices)	8,503	11566.98	18676.87	132.30	194188.2
GDP per Capita Growth Rate	8,531	2.133	6.155	-64.99	140.37
Democracy Score	8,277	1.031	7.400	-10	10
Urban Population	8,081	7643.33	26982.78	0	612933
Total Population (1000s)	8,081	31607.50	113992.1	16	1377065
Ethnic Fractionalization	7,363	0.43884	0.26902	0	0.89
Life Expectancy	10,398	63.78	11.48	18.91	85.42
Material Capability Index	8,081	0.00628	0.02080	5.85E-07	0.218117
Military Expenditure/ GDP	6,797	2.84	3.31	0	117.35

Table AP1-4 Full Results for Conflict Termination Models

	Model AP1-4.1	Model AP1-4.2	Model AP1-4.3	Model AP1-4.4
		Intervention- Level Effect		
Variables	**Probit**	**Probit**	**Conditional Mixed Process**	**Probit (Conflict-affected countries sample)**
Neutral HMIs	0.757***	0.663***	0.673***	0.615***
	(0.00)	(0.01)	(0.00)	(0.02)
Against Government HMIs	0.236	0.242	0.416	0.268
	(0.83)	(0.82)	(0.71)	(0.81)
Against Rebels HMIs	0.413	0.387	0.182	0.217
	(0.31)	(0.34)	(0.62)	(0.58)
New Conflict	1.92	1.91	1.85	1.84
	(0.00)	(0.00)	(0.00)	(0.00)
New Conflict$_{t-1}$	0.663	0.662	0.702	0.606
	(0.00)	(0.00)	(0.00)	(0.00)
Logged Total Population	0.239	0.118	0.138	-0.030
	(0.01)	(0.24)	(0.02)	(0.77)
Logged Urban Population	-0.008	0.113	0.047	0.184
	(0.91)	(0.17)	(0.38)	(0.03)
Ethnic Fractionalization	0.632	0.113	0.279	0.019
	(0.00)	(0.68)	(0.08)	(0.94)
Material Capability	-11.80	-9.48	-9.57	-9.28
	(0.01)	(0.04)	(0.01)	(0.02)
Military Expenditure/GDP	0.023	0.023	0.026	0.033
	(0.00)	(0.00)	(0.00)	(0.00)
Regional Dummies	No	Yes	Yes	Yes
Wald- LR Statistic /Prob > chi2	248.41	254.73	771.00	222.70
	(0.00)	(0.00)	(0.00)	
Observations	5152	5152	5152	3511

Chapter 2
The Impact of Drone Warfare on Suicide Bombings in Pakistan

2.1 Introduction

The United States, effectively, went to war against Al Qaeda and affiliated militants after the September 2001 attack. Along the way, the Bush administration reinstated a policy, which had been banned since 1976, of targeted assassinations by the US military and the Central Intelligence Agency (CIA) to eliminate overseas actors deemed to be hostile (Williams, 2010). The US also introduced unmanned aerial vehicles (UAVs), also known as drones, into this assassination campaign. Drones are widely viewed as an attractive weapon because of their relatively low cost, surveillance capabilities, ability to strike precise GPS points, and the safety of their operators from life-threatening risks.[1]

The Waziristan region of what was formerly known as the Federally Administered Tribal Areas (FATA) of Pakistan has been a focus for US drone activity with the CIA leading a hunt for Al Qaeda members and allies.[2] The database of the New America Foundation records 414 drone strikes in the FATA targeting a variety of militant groups.[3]

Recent scholarly literature is divided about the impact of the US drone program in Pakistan. Johnston (2012), Johnston and Sarbahi (2016), and Mir and Moore (2018) argue that drone strikes have tended to suppress militant violence while Jaeger and Siddique (2018), Mahmood and Jetter (2019), and

[1] Military drones can stay airborne for over 24 hours and are cheaper than fighter jets. Predator and Reaper drones cost around $4.5 million and $22 million, respectively, whereas F-16's and F-35's cost $47 million and $148-$337 million, respectively. General David Deptula described drones as offering the promise "to project power without projecting vulnerability" (Gusterson, 2016).
[2] The FATA was a federally administered tribal area of Pakistan bordering Afghanistan and consisting of seven agencies (North Waziristan, South Waziristan, Kurram, Orakzai, Khyber, Mohmand and Bajuar) until it was officially merged with the Khyber Pakhtunkhwa province in 2018. The drone program in the region was almost entirely run by the CIA, a prime exception being the May 2016 killing of Taliban leader Mullah Akhtar Mohammad Mansour in Baluchistan which was carried out by the US military (Feffer, 2016).
[3] For more information see https://www.newamerica.org/in-depth/americas-counterterrorism-wars/pakistan/

Rigterink (2021) argue, broadly, that the strikes may have been counterproductive. We consider exactly this question of whether or not these strikes have been effective in deterring violence. Our main innovation is to use variation in cloud cover and precipitation plus the closure of a drone base to instrument for drone strikes, thereby addressing an endogeneity issue that plagues efforts to identify a causal relationship between drone strikes and militant violence.[4] A second contribution is that we account for spatial heterogeneity in the distribution of suicide bombings. Third, we eliminate noise by focusing specifically on suicide bombings, the weapon of choice for the Islamist militants the CIA targets with its drone strikes.[5] We find that drone strikes cause at least one suicide attack, on average, within the ensuing month which is likely to occur within a 0-400 kilometer radius of the strike point. We calculate that roughly 27-33 percent of suicide bombings in Pakistan between July 2008 and the end of 2016 are attributable to drone strikes.

2.2 The US Drone Program in Pakistan

2.2.1 Background

Drones are not new to the battlefield. For example, Iran used primitive drones to fire rocket-propelled grenades during the Iran- Iraq war in the 1980s (Gusterson, 2016). But in the 21st century, the US has mobilized its technologically sophisticated Predator and Reaper drones into campaigns that are unprecedented in their sheer scale and capabilities.[6]

The CIA's first drone strike in Pakistan killed Taliban leader Nek Muhammad in South Waziristan (Mazetti, 2013) in June of 2004 after fighting in Afghanistan had prompted some Taliban and Al Qaeda fighters to relocate to the FATA and use it as a launching pad for attacks in both Afghanistan and

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[4] Mahmood and Jetter (2019) use wind speed in an instrumental variables approach that is similar in spirit to our use of cloud cover.

[5] We think that focusing on suicide attacks eliminates some noise when one lumps together various attack types; some of which, such as assassinations of leaders of competing ethnic groups, are unlikely to be driven by drone strikes.

[6] Predator drones, first developed in the 1990's, weigh just 1130 pounds, can fly up to 25,000 feet, and as fast as 135 miles per hour. Normally equipped with two Hellfire missiles, predators can stay airborne for 24 hours. The Reaper drones are still higher in quality, attaining twice the top speed and altitude of the Predators and carrying more missile types (Gusterson, 2016).

Pakistan (Shahzad, 2011). International pressure and militant bombing campaigns within Pakistan then led the Pakistani government to overcome its initial reluctance to expel militants from these areas (Aslam, 2011) and the CIA was allowed to initiate a parallel and complementary campaign to target militants in the region using combat drones. The drone campaign started slowly with 9 strikes during 2005-2007 but then picked up pace as the Bush administration dramatically increased to 36 strikes in 2008.[7] The number of strikes then ballooned up to 122 in 2010 alone and remained high until falling back to just 10 in 2015 and progressing to single digits until 2018.

The US maintains that drones decapitate militant organizations and disrupt their activities through precision strikes that do not put American lives at risk. Johnston and Sarbahi (2016), Mir and Moore (2018), Byman (2013), and Horowitz, Kreps, and Fuhrmann (2016)) all make cases for drone programs broadly in these terms.[8] However, critics argue that drone strikes breach international law, especially in countries like Pakistan and Somalia that are not officially at war with the US. They also stress collateral effects such as civilian fatalities (Lamb, Woods and Yusufzai, 2012), mental trauma suffered by residents of areas targeted through drones (Stanford Law School and New York University School of Law, 2012), and injury to the legitimacy of the governments of countries where the US makes drone strikes (Boyle, 2013). Finally, several recent papers argue that drone strikes are counterproductive, blowing back into increased violence against the US and its allies (Feffer, 2016; Jaeger and Siddique, 2018; Mahmood and Jetter, 2019; Rigterink, 2021). Our paper focuses on potential blowback, specifically taking the form of suicide attacks that might be connected with drone strikes in Pakistan.

2.2.2 Descriptive Statistics on Drone Strikes and Suicide Bombings

The database of the New America Foundation, (Bergen, Sterman, & Salyk-Virk, 2021), shows a sharp rise and subsequent fall in drone-strike frequency under Obama (Table 2.1 & Figure 2.1) with a much

[7] William (2010) argues that Bush's failure to seek Pakistan's consent for the US drone programme in Pakistan fed a subsequent spike in suicide attacks. Interviews by Mir and Moore (2018) suggest, however, that President Musharaf did secretly sanction the increase in strike frequency while he was under pressure after the assassination former prime minister Benazir Bhutto. Of course, targeted organizations would not have been privy to such a secret agreement so William (2010) could still be right.

[8] The program had operated for about 10 years before it was officially acknowledged in 2012. Yet it was an open secret with then CIA Director Leon Panetta commenting back in 2009 that "Very frankly, it's the only game in town in terms of confronting or trying to disrupt the al Qaeda leadership" (Williams, 2010)

smaller spike in civilian casualties (Table 2.1). Drone strikes under Obama appear to have been more precisely targeted on militants (Table 2.1), an outcome that Gusterson (2016) attributes to better technology, such as Reaper drones, and tighter protocols governing the strikes.[9] In addition to the moral advantages of better targeting, one might expect more precise strikes to be more effective at countering militant violence than less precise strikes are. On the other hand, the database credits the Bush-era strikes with killing 0.35 militant leaders per strike compared to just 0.18 for the Obama era, although the former comes at the cost of 7-8 civilians killed per militant leader compared to around 2 for the latter. Gusterson (2016) suggests that the new Obama policy of "signature strikes," i.e., monitoring the behavior of suspects who are then struck if their behavior is found to be consistent with militancy, can largely explain the differences between the Bush and Obama administrations where the former executed strikes based on pre-decided kill lists (Gusterson, 2016). The observation period of the signature strikes seems to have saved the lives of civilians while expanding targeting to include more low-ranking militants than had previously been the case.

Table 2.1 Comparative Statistics of Drone Strikes

	Bush	**Obama**	**Trump**	**Total**
Total Strikes	48	353	13	414
Civilian Casualties	116-137	129-162	0-4	245-303
Militant Casualties	218-326	1659-2683	33-62	1910-3071
Unknown Casualties	65-77	146-249	0-2	211-328
Total Casualties	399-540	1934-3094	33-68	2366-3702
Civilian Casualties Per Strike (Min)	2.42	0.37	0.00	0.59

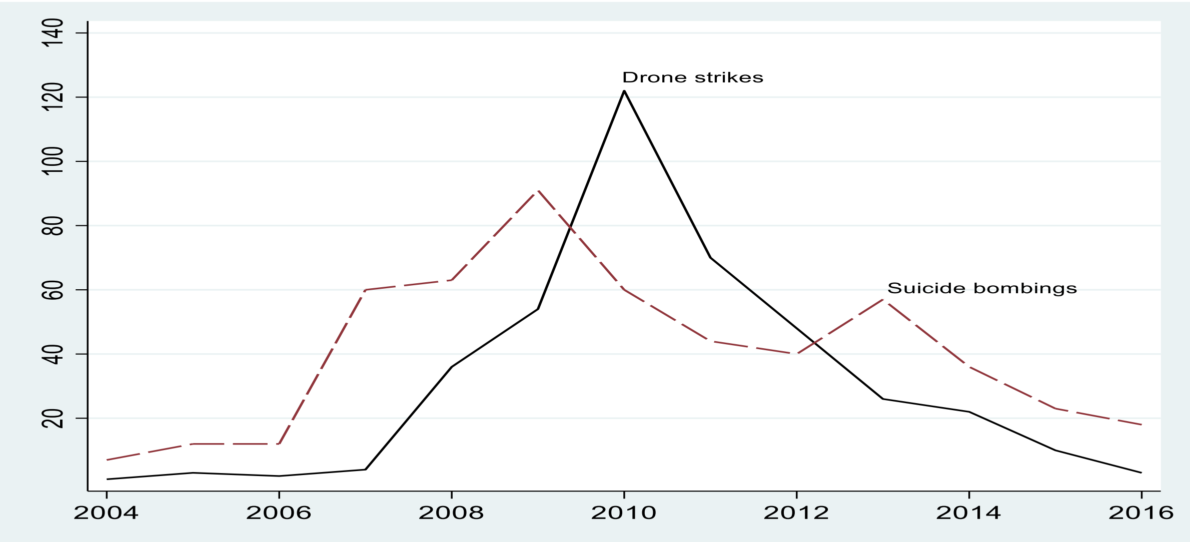
[9] The Reaper are designed to carry not just Hellfire missiles but also more precise and smarter missiles. The rules for drone strikes were also made stringent in May 2013 after pressure from Human Rights groups and few European countries intensified.

Civilian Casualties Per Strike (Max)	2.85	0.46	0.31	0.73
Militant Casualties Per Strike (Min)	4.54	4.70	2.54	4.61
Militant Casualties Per Strike (Max)	6.79	7.60	4.77	7.42
Total Casualties Per Strike (Min)	8.31	5.48	2.54	5.71
Total Casualties Per Strike (Max)	11.25	8.76	5.23	8.94

Data source: (Bergen, Sterman, & Salyk-Virk, 2021)

Suicide bombing trends track drone strike trends fairly well (Figure 2.1).

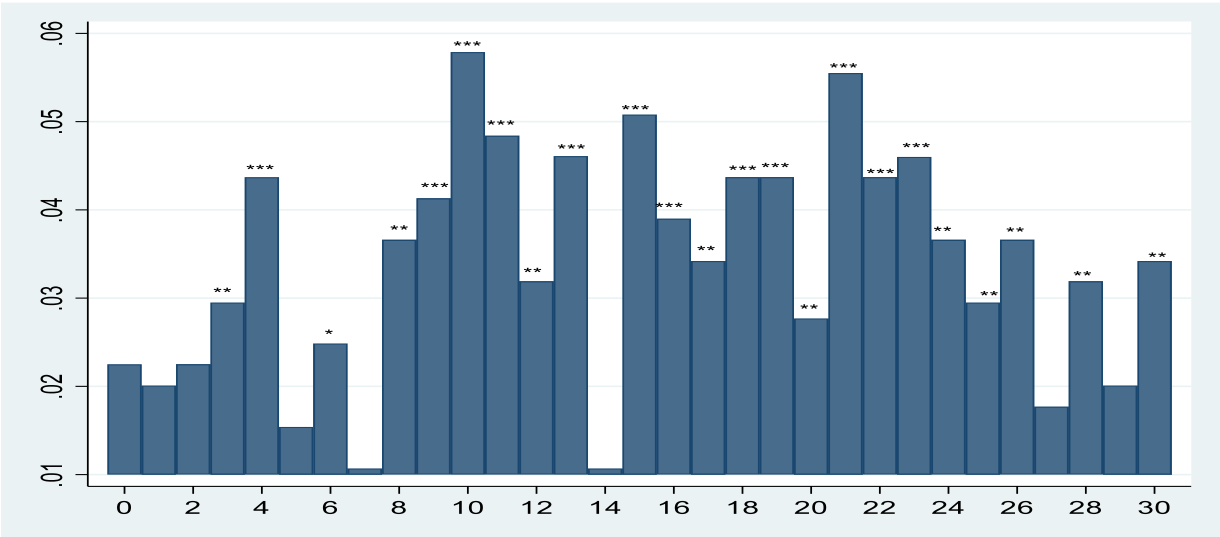
Figure 2.1 Trends in Drones Strikes and Suicide Bombings in Pakistan



Data sources: Drone Strikes: New American Foundation database on drone strikes in Pakistan. Suicide bombings: Chicago Project on Security and Threat, University of Chicago.

Moreover, following the methodology presented in Jaeger and Paserman (2008), Figure 2.2 shows the average numbers of suicide bombings for days X after drone-strike days minus the overall average of drone strikes per day over the whole period for all X between 1 and 31 days. We see elevated rates of suicide attacks throughout these drone-strike aftermaths with many statistically significant differences appearing three days after the drone strike. Saeed, Spagat, and Overton (2019) show that these deviations sum roughly to 1, implying one extra suicide attack within a month of a drone strike. Or, more conservatively, the sum of the statistically significant deviations is around 0.68. So drone strikes do appear to be associated with elevated suicide bombing rates although we cannot make a good causal claim based on this analysis.

Figure 2.2 Mean Deviations of Average Suicide Bombings Over 31 Days Following Drone Strikes



*The numbers represent deviations of the average number of suicide bombings on X days after drone strikes from the overall average number of suicide bombings. ***, ** and * indicate statistical significance at 1 %, 5 % and 10 % respectively. Data sources: Drone Strikes: New American Foundation database on drone strikes in Pakistan. Suicide bombings: Chicago Project on Security and Threat, University of Chicago.*

2.3 Literature and Hypotheses

The relevant literature divides along two distinct lines. The first divide is on the question of whether drone strikes deter or incite violence. The second divide is over methodology; some study local public opinion over drone strikes while others study the dynamics of strikes and militant violence.

Our paper focuses on the violent dynamics but here we pause briefly to consider the public opinion literature. A 2014 PEW survey found that 2 Pakistanis in 3 oppose drone strikes, suggesting rather strong opposition to the policy (Pew Research Center, 2014). [10] However, this survey did not cover the tribal areas where, plausibly, support for drone strikes that rid these areas of local violent actors could

[10] See detailed survey at https://www.pewresearch.org/global/2014/08/27/a-less-gloomy-mood-in-pakistan/

be much stronger than it is in the rest of the country. Nevertheless, a 2010 survey that covered tribal populations found that a whopping 90% of the population opposed US military operations in the region (Ballen, Bergen, and Doherty, 2010). Shah (2018), on the other hand, criticized the PEW survey for its incomplete coverage and the Ballen, Bergen, and Doherty (2010) survey for "social desirability bias," i.e., that respondents feared retaliation from militants if they failed to oppose drone strikes. Shah (2018) asked North Waziristan residents whether drone strikes created new militants and found that 71 percent of his respondents disagreed while only 8 percent agreed with the rest being unsure. At first glance, the results of Shah (2018) seem to be in strong conflict with the previous survey work although many people can simultaneously oppose drone strikes while not believing that they do not incite people to join militant groups. Moreover, the sample of Shah (2018) appears to be rather biased towards sections of the tribal society such as tribal elders, maliks (official headmen), lawyers, reporters, officials, and students who are the sort of people who the Taliban target and may, therefore, be more likely than the rest of the population to support drone strikes. Even so, the contrast between findings from tribal and non-tribal population samples in Shah (2018) and (Pew Research Center, 2014) survey is striking. Silverman (2018) suggests that people in tribal areas may better understand the positive effects of the drone strikes in their region than people living outside the region do and that knowledge of and support for drone strikes goes hand in hand. We make no attempt to resolve these disagreements here and simply note that average levels of public support for drone strikes are, at best, one factor among several in driving the dynamics of violence in Pakistan. It is, for example, possible that large numbers of Pakistanis are supportive of drone strikes while, simultaneously, a small sliver of society hates them so passionately that they are driven into the arms of militant groups.

Johnston and Sarbahi (2016) and Mir and Moore (2018) operate within the violence dynamics branch of the literature, both finding that drone strikes deter militants' violence within the tribal areas and vicinity. Mir and Moore (2018) find that the whole drone program made a major contribution to deterring violence, with 75 percent of this violence-suppressing impact coming from the anticipatory effect of drone strikes which, they argue, changed the behavior of militants by, for example, restricting their movements and breaking down internal trust. In contrast, Johnston and Sarbahi (2016) focus, in contrast, on the effect of individual drone strikes which, they find, led to around a 5 percentage points decrease in the terrorist incidents. Both of these studies look for reactions only nearby to where drone strikes occur and not further afield in Pakistan. Yet Saeed and Syed (2016) find that militants emerge from a variety of geographical areas in Pakistan, not just the tribal ones. Thus, one might expect drone strikes to incite reactions throughout Pakistan, not just in the tribal areas where they occur. Indeed, Jaeger and Siddique (2018), consider reactions throughout Pakistan and do find evidence of militant reaction within a week following drone strikes.

All of the above works on drone-militant dynamics rely on an assumption that drone strikes are exogenous events although there is good reason to question this assumption. First, Islamabad clandestinely coordinates the drone campaign with the CIA. Pakistani intelligence agencies serve up militants as CIA targets whom they know to have perpetrated violence within Pakistan.[11] Thus, there is a plausible channel of causation running from militant attacks to drone strikes, operating through Pakistani intelligence agencies and the CIA. Second, the activity of both militant violence and drone strikes can plausibly be affected by some common underlying factors such as group sizes of militant organizations and locations and episodes of infighting. Failure to account for these factors can cause correlations between the error terms in econometric models meant to explain militant violence and the drone strike variable used as an explanatory variable in these models.

Mahmood and Jetter (2019) address this endogeneity problem by using wind speed as an instrument for drone strikes. They find, in contrast to Johnston and Sarbahi (2016) and Mir and Moore (2018), that 1 drone strike generates roughly 4 terrorist attacks over the subsequent 7 days and that drone strikes

[11] Pakistan has always officially denied its involvement in the drone program. However, there is ample evidence to suggest otherwise. Miller and Woodward (2013) quote from CIA documents and Pakistan's diplomatic memos that Pakistani officials were regularly briefed about the drone strikes. On the 12th of February 2009, Dianne Feinstein, Chair of the Senate Intelligence Committee, acknowledged that drones were flying from an air basee within Pakistan. Indeed, the *Times* later published images from Google Earth showing drones parked at Shamsi Airbase in Baluchistan, Pakistan, implicating the Pakistan military in the program (Page, 2009). President and former Army Chief Pervez Musharraf admitted in a 2013 CNN interview that Pakistan did consent to some drone strikes while Mir and Moore (2018) quotes officials from the US and Pakistan reporting that Musharraf offered the CIA a "flight box" over North Waziristan. Even Pakistan's civilian leadership had no qualms about the drone program; an August 2008 cable, published by Wikileaks, quotes the Prime Minister of Pakistan Yusuf Raza Gilani telling US Ambassador Anne Patterson that "I don't care if they do it as long as they get the right people. We'll protest in the National Assembly and then ignore it." For more see Mir and Moore (2018), Robertson and Botelho (2013), Mazetti (2013) and Miller and Woodward (2013)

explain around 16 percent of all terrorist incidents within Pakistan between 2006 and 2016. Rigterink (2021) uses success versus failure of attempts to assassinate top terrorist leaders with drone attacks as quasi-random outcomes to identify a causal effect of drone strike hits on subsequent terrorist attacks.

Our work differs from Mahmood and Jetter (2019) in three main ways. First, we consider a range of potential instruments and find that cloud cover, precipitation, and the date of a major drone base closure in Pakistan outperform wind speed as instruments for drone strikes. Second, we focus exclusively on suicide bombings which are the best documented and most lethal method of militant violence, particularly against targets such as military or foreign installations due to their international connections. Third, we also account for spatial variation in the distribution of suicide bombings carried out in response to drone strikes. The identification strategy of Rigterink (2021), hits versus misses, is entirely different from both ours and that of Mahmood and Jetter (2019) while our other differences from the latter paper also apply to the former one which also considers other questions such as impacts on the types of terrorist attacks.

The above discussion shows that the existing evidence is mixed on whether drone strikes are effective in countering terrorism. However, one side of the argument does maintain that drone strikes can disrupt and degrade terrorist networks and hence affect their ability to perpetrate violence (Johnston, 2012: Johnston and Sarbahi, 2016; Mir and Moore, 2018). This leads to our first hypothesis:

Hypothesis 1A: *All else equal, drone strikes lead to a reduction in suicide bombing.*

On the other hand, patterns in suicide bombing following drone strikes in Pakistan are suggestive of the blowback effect (Figure II: Jaeger and Siddique (2018): Mahmood and Jetter, 2019: Rigterink, 2021). The theoretical argument in support of these patterns is that drone strikes kill innocent people, not just the militants, and hence incite anger, national outrage, and result in violence (Kilcullen and Exum, 2009, Feffer, 2016). This leads to the second hypothesis:

Hypothesis 1B: *All else equal, drone strikes lead to an increase in suicide bombing.*

In the next section, we outline the econometric methodology we use to test the causal impact of drone strikes on suicide bombings.

2.4 Econometric Methodology

We assess the impact of drone strikes on suicide bombing using regression analysis. However, the standard Ordinary Least Squares (OLS) approach, illustrated in equation (1) below, is inadequate due to endogeneity problems (Green, 2003):

$$SuicideBombing_t = \beta_0 + \beta_1(Drones)_t + X_t^{`}\beta \quad + \varepsilon_t \qquad (1)$$

where $X_t^{`}$ is a matrix of control variables and ε_t is an error term. Specifically, the error term in a regression of suicide bombings on drone strikes could be correlated with the drone-strike variable, rendering the OLS estimates to be biased.

Reasons for endogeneity problems abound. First, there is measurement error in part because we must extract our data from imperfect news stories. Second, there may be reverse causation whereby suicide bombings also cause drone strikes, in part because suicide attacks provide information on the possible whereabouts of terrorist groups while also exerting pressure for responses. Third, both suicide bombings and drone strikes may be affected by common factors that are omitted from the regression. For instance, reports of infighting amongst militant groups could affect their capacity to carry out suicide bombings while at the same time increasing their visibility and, hence, vulnerability to drone strikes (Craig & Khan, 2014). If the true effect of drone strikes on suicide bombings is negative, then omitting infighting amongst militant groups variable will cause negative bias in the estimate whereas if the true effect is positive, then it will cause positive bias. The size of the militant groups is also likely to positively correlate with drone strikes and if the true effect of drone strikes on suicide bombings is negative, then omitting this variable will cause negative bias and vice versa. Other factors such as the geographical locations of militant groups' strengths might simultaneously affect both suicide bombings and drone strikes. Governments and militant groups are unlikely to share detailed information on such factors so they are unobservable and, therefore, not included in estimated models. OLS estimation of equation 1 can, therefore, lead to errors in the signs, magnitudes, and p values of our estimates.

We use cloud cover, precipitation and a dummy for the closure of a drone base in Pakistan as instruments for drone strikes to counter the endogeneity issues. Weather conditions affect the flying and targeting capabilities of drones (Mahmood and Jetter, 2019; C., Wood, personal communication, March 02, 2019; J., Bronk, personal communication, March 06, 2019; W., Zwijnenburg, personal communication, March 07, 2019; United States Government Accountability Office, 2017; Gusterson, 2016; Whitlock, 2014; Fowler, 2014).[12] Drone operators gather evidence through live camera surveillance (Gusterson, 2016).[13] Cloud cover and related conditions, such as rain, impede this camera-based surveillance and also hinder take-offs and landings.[14] Also, the missiles in use for Predator and Reaper drones during the period we cover, such as the GBU-12 and the AGM-114 Hellfire, require clear lines of sight for targeting.[15] Hence cloud cover and rain, as measured through precipitation, are important factors that influence both visual monitoring and immediate combat capabilities for drones. At the same time, clouds and precipitation should not directly affect suicide attacks. Thus, these two weather variables appear to be excellent candidates for instruments, either alone or in combination. We also use a qualitatively different instrument in the form of a dummy variable for the closing of Shamsi airbase in the Baluchistan province of Pakistan on November 26, 2011.[16] NATO had just accidentally killed 24 Pakistani soldiers at a checkpoint on the Pakistan-Afghan border and Pakistani officials felt pressure to take visible action against the US. Shamsi base was a workhorse facility for surveillance and combat drone missions at that time and its closure compromised drone operations without directly affecting suicide attacks.

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[12] We corresponded with Chris Woods (Director Airwars), Justin Bronk (Research Fellow/Editor Royal United Services Institute, Royal United Services Institute for Defense and Security Studies) and Wim Zwijnenburg (Program Leader Humanitarian Disarmament, PAX for Peace) and received valuable input about how weather conditions such as cloud cover can affect targeting through these missiles.

[13] Other than the camera, the sensor ball also contains equipment for capturing mobile signals on the ground (Gusterson, 2016). See BBC's report on how drone works at *https://www.bbc.co.uk/news/world-south-asia-10713898*

[14] According to the United States Government Accountability Office, 20 percent of Predator B mission cancellations during 2013-2016 period were due to these weather conditions (United States Government Accountability Office, 2017).

[15] GBU-12 and AGM-114 are semi-active laser homing missiles and cloud cover can cause beam distortion and attenuation for the spotting laser which the weapons home in on (C., Wood, personal communication, March 02, 2019; J., Bronk, personal communication, March 06, 2019; W., Zwijnenburg, personal communication, March 07, 2019).

[16] See Henderon, (2011) and Dawn, (2011) for more on Shamsi airbase closure.

Our first-stage model is:

$$Drones_t = \alpha_0 + \alpha_1 (cloud\,\mathrm{cov}\,er * precipitation)_t + \alpha_2 (BaseClosure)_t + X_t^{`}\alpha \;+ \gamma_t$$

Where X is a matrix of control variables and γ is the error term

The second-stage equation incorporates the predicted values for drones from the first-stage model as an independent variable.

$$SuicideBombing_t = \beta_0 + \beta_1 (pr.Drones)_t + X_t^{`}\beta \quad + \varepsilon_t$$

We employ Limited Information Maximum Likelihood (LIML), Generalized Method of Moments (GMM), and Two-Stage Least Square (2SLS) estimators for this final equation with each method offering some advantages. 2SLS is simple, intuitive and widely understood while GMM is suitable for over-identified models and LIML, which is asymptotically equivalent to 2SLS, outperforms 2SLS with weak instruments and also exhibits smaller bias than the other estimators (Cameron and Trivedi, 2009).

2.5 Data Sources

2.5.1 Dependent Variables: Suicide Bombings

The data for incidents and casualties in suicide bombings is taken from Chicago Project on Security and Threats (CPOST), University of Chicago, database. The CPOST database is one of the most prolific and widely used data repositories on suicide bombings.

2.5.2 Instrumented Variable: Drone Strikes Incidence and Casualties

The data for drone strike incidents and casualties are taken from New America Foundation (NAF) database which records 414 drone strikes in Pakistan between 2004 and 2018. The Bureau of Investigative Journalism (BIJ) and the Long War Journal (LWJ) are alternative sources, recording 430 and 404 drone strikes, respectively, during the same period. However, we use the NAF database because it provides detail not just on civilian casualties but also on the identities of militant leaders, enabling an analysis of the impact of drone strikes that kill leadership figures leaders on suicide bombings.

2.5.3 Instrumental Variables: Cloud Cover, Precipitation, and a Dummy for a Drone Base Closure

The data for cloud cover and precipitation comes from World Weather Online which is one of the largest online repositories of weather data covering approximately 3 million cities/towns worldwide.[17] Cloud cover is measured as the percentage of the sky covered by clouds. Total precipitation is measured in millimeters. The dummy for drone base closure is 0 before November 26, 2011, and 1 afterward. We purchased weather data for just North Waziristan which experienced 70 percent of all drone strikes in Pakistan between July 2008 and December 2016.[18] Accordingly, our empirical analysis includes only drone strikes in North Waziristan.

2.5.4 Other Control Variables

Controls include dummies for the holy months of Ramadan and Muharram, Parliamentary election periods, and three military offensives by Pakistan's military. Islamic tradition discourages fighting during the month of Ramadan, possibly explaining some variation in suicide bombings (Jaeger and Siddique, 2018). Muharram is also an important religious month, particularly for Shiites, who march in processions in remembrance of the death of Prophet Muhammad's grandson Hussain. Many Sunni militants in Pakistan consider Shiites to be heretic and target them, particularly during this month, sometimes with suicide bombs. Pakistani militants oppose parliamentary forms of government and, hence, can be expected to launch suicide attacks for subversion during election periods.[19] The major Pakistani military operations known as *Zarb e Azab* (Sharp and Cutting Strike), *Rah-e- Haq* (Just Path), and *Rah-e-Rast* (Righteous Path) can be expected to influence suicide bombings.[20] Staniland, Mir, and

[17] See https://www.worldweatheronline.com/aboutus.aspx for more information.
[18] We are restricted to this time period because world weather online data for North Waziristan starts from July 2008 and suicide bombing data terminates in 2016.
[19] For more on Taliban's threat to elections see (Farhan & Mallet, 2013)
[20] The time periods for the three offensives in our models are 2014 to the end of our study period, September 2007 to February 2009 and May 2009 to July 2009 for *Zarb e Azab, Rah e Haq and Rah e Rast* respectively.

Lalwani (2018) provide the dates for these operations. Our final controls are dummies on the years 2011, 2012 and 2013 [21]

We report descriptive statistics for all the variables in Appendix 2.

2.5 Results

2.5.1 The Main Results

Table 2.2 shows second stage estimates, with time resolved down to the weekly level, using Limited Information Maximum Likelihood (LIML), Generalized Method of Moments (GMM), and Two-Stage Least Square (2SLS) estimators. Drone-strike coefficients are always positive with significance levels between 10% and 1%. The magnitudes of the estimates are large, ranging between 0.37 and 0.43, suggesting that every three drone strikes cause more than one suicide bombing within a week on average. Although one should not focus much attention on coefficient estimates for control variables it does seem worth noting that the *Zarb-e-Azab* offensive does seem to be associated with a sharp drop in suicide bombings. The instruments appear to be quite strong with the first stage F statistics much larger than the conventional benchmark of 10 and the minimum eigenvalue statistics (Cragg and Donald, 1993) larger than critical values corresponding to minimum toleration of 5 percent bias.[22] The final column in table 2.2 suggests that each drone strike causes roughly 10 suicide bombing deaths on average, a large effect indeed.

The sign of the estimate for drone strikes in the OLS model has a positive sign and weak statistical significance of 10 percent (Table 2.2). Roughly, this is in line with the findings in Johnston (2012), Johnston and Sarbahi (2016), and Mir and Moore (2018). However, results from several diagnostics tests show that we are justified in considering drone strikes as an endogenous covariate in the model for suicide bombings therefore the estimate from OLS estimation is not reliable

[21] We do not use dummies for years 2008, 2009, 2010, 2014, 2015 and 2016 due to the high correlation of these dates with military operations.
[22] This bias percentage reflects the magnitude of the bias from IV estimators that one is willing to tolerate relative to the bias from the OLS estimator.

Table 2.2 Instrumental Variable Regressions (Week-Level Contemporaneous Impact)

	Dependent Variable: Number of Suicide Bombings						D.V= Number of Fatalities in Suicide Bombings
Variables	**OLS**	**LIML**	**GMM**	**LIML**	**GMM**	**2SLS with Newey-West S.E**	**2SLS with Newey-West S.E**
Drone Strike	**-0.091 (0.10)**	**0.453*** (0.00)**	**0.429*** (0.00)**	**0.381*** (0.01)**	**0.372*** (0.01)**	**0.379** (0.04)**	**9.87*** (0.00)**
Other Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	No	No	Yes	Yes	Yes	Yes
1st Stage F stat		20.86	20.86	45.85	45.85	45.85	41.92
Minimum Eigen Statistic		27.06	27.06	23.43	23.43	23.43	21.89
F Stat/Wald chi2	14.74	65.71	66.37	74.35	75.06	74.42	38.39
Prob>Chi2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
No. of Obs	441	441	441	441	441	441	441

F stat reported for OLS Model. Constant included in all models. Parentheses contain p values.
**** p< 0.01, ** p< 0.05 and * p<0.10.*

Table 2.3 gives results from further diagnostic tests. The endogeneity test of Baum. Schaffer and Stillman (2007) reject in all models the null hypothesis that drone strikes are exogenous, thereby supporting our initial premise that research needs to address the endogeneity of drone strikes.[23] Next, we consider the requirement that our instruments should be correlated with drone strikes but not with the error terms in the estimated equations. Indeed, our Anderson-Rubin and Hansen J tests (Cameron

[23] This test is implemented in Stata and is based on the difference of two Sargan-Hansen statistics. These statistics are obtained by first estimating an equation that treats suspect regressors as endogenous and then another equation that treats them exogenous. The test is the numerical equivalent of the Hausman test under conditional homoscedasticity.

and Trivedi, 2009; Baum, Schaffer, and Stillman, 2007), which are compatible with all of our models, reject the hypothesis of correlations between the instruments and the error terms in all models. Next, we perform Montiel-Pflueger tests, which are robust to both heteroscedasticity and autocorrelation (Olea and Pflueger, 2013), as further checks for the possible weakness of our instruments. We reject the weak instrument hypothesis in all cases. Finally, we employ the LM redundancy test to check whether we may be using too many instruments (Baum, Schaffer, and Stillman, 2007) and always reject the hypothesis of redundant instruments.

To summarize, Tables 2.2 and 2.3 support the blowback idea encapsulated in hypothesis 1B, and this finding is robust to a wide range of diagnostic tests.

Table 2.3 Results for Diagnostic Tests

	LIML	**GMM**	**LIML**	**GMM**	**2SLS**	**2SLS**
Test for Endogeneity H_0= Drone strikes and Base Closure are exogenous	10.10 (0.001)	7.40 (0.006)	10.10 (0.005)	7.42 (0.006)	7.40 (0.006)	9.04 (0.002)
Over-identification Test H_0= CloudCover *Precipitation and Drone Base Closure uncorrelated with the error	Anderson-Rubin chi	Hansen J	Anderson-Rubin chi	Hansen J	Hansen J	Hansen J
	0.344 (0.55)	0.535 (0.46)	0.163 (0.68)	0.261 (0.60)	0. 535 (0.46)	2.61 (0.46)
Weak Instrument Test H_0= Instruments are weak	Montiel Pflueger Effective F Statistic	Montiel Pflueger Effective F Statistic	Montiel Pflueger Effective F Statistic	Montiel Pflueger Effective F Statistic	Montiel Pflueger Effective F Statistic	Montiel Pflueger Effective F Statistic
	27.12	27.12	43.90	43.90	27.12	43.90
LM Test of Instrument Redundancy H_0= Instrument is redundant	1-Cloud cover * Precipitation = 5.97 (0.01) 2- Base closure =29.02 (0.00)					

We now repeat our analysis but change the time resolution to two-week periods (Table 2.4). The results are broadly consistent with what we found at 1-week time resolution, although the coefficients on drone attacks are now slightly smaller, in a range of 0.33 to 0.39 and less significant.

Table 2.4 Instrumental Variable Regressions (Two-Week Level Contemporaneous Impact)

`	Dependent Variable: Number of Suicide Bombings					D.V= Number of Fatalities in Suicide Bombing
Variables	**LIML**	**GMM**	**LIML**	**GMM**	**2SLS with Newey-West S.E**	**2SLS with Newey-West S.E**
Drone Strike	0.369** (0.03)	0.391** (0.02)	0.329* (0.05)	0.334* (0.05)	0.326* (0.09)	9.21** (0.01)
Other Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	No	No	Yes	Yes	Yes	Yes
Root MSE	1.689	1.707	1.642	1.646	1.640	32.70
1st Stage F stat	16.37	16.37	24.33	24.33	24.33	20.78
Minimum Eigen Statistic	19.57**	19.57**	16.56**	16.56**	16.55**	14.89*
Wald chi2	80.95	80.03	84.85	84.85	84.97	39.40
Prob>Chi2	0.00	0.00	0.00	0.00	0.00	0.00
No. of Obs	221	221	221	221	221	221

Constant included in all models. Parentheses contain p values. **** $p< 0.01$, ** $p< 0.05$ and * $p<0.10$.*

Table 2.5 repeats our 2SLS analysis but with time divided, first, into three-week periods and, second, into four-week periods following week t. This enables us to capture the follow-up impact of the drone strikes. The exact equations estimated are,

$$SuicideBombing_{t1+t2+t3} = \beta_0 + \beta_1(pr.Drones)_t + \grave{X}_t\beta \quad + \varepsilon_t$$

$$SuicideBombing_{t1+t2+t3+t4} = \beta_0 + \beta_1(pr.Drones)_t + \grave{X}_t\beta \quad + \varepsilon_t$$

The results, combined with the previous ones, suggest that much of the reaction to drone strikes is loaded into the last two weeks of the four-week aftermath. The coefficient on drone strikes exceed 1 already within the three-week window and rises to around 1.5 within the four-week window. These estimates are reminiscent of, but substantially larger than, the findings shown in figure 2.2 that did not account for endogeneity. These results further strengthen the evidence for the blowback thesis.

Table 2.5 Instrumental Variable Regression (Follow-up Impact)

	Dependent Variable Number of Suicide Bombings In period t+ 3 weeks		**Dependent Variable Number of Suicide Bombings In period t+ 4 weeks**	
Variables	**2SLS with Newey West S.E**	**2SLS with Newey West S.E**	**2SLS with Newey West S.E**	**2SLS with Newey West S.E**
Drone Strike	1.15** (0.02)	1.10** (0.01)	1.48** (0.02)	1.45** (0.01)
Other Control Variables	Yes	Yes	Yes	Yes
Time Dummies	No	Yes	No	Yes
F stat	12.62	10.23	13.60	11.32
prob>f	0	0	0	0
No. of Obs	442	442	442	442

Constant included in all models. Parentheses contain p values. **** p< 0.01, ** p< 0.05 and * p<0.10.*

2.5.2 Decapitation Effects

We now focus attention just on drone strikes that eliminate militant leaders, i.e., so-called "decapitation" strikes. Jordan (2009) argues that the effectiveness of decapitation strikes depends upon a constellation of factors, such as group size, age, and effectiveness in replacing leadership while Pape (2003) finds little evidence of their effectiveness in his study on suicide terrorism. On the other hand, Johnston (2012), accounting for endogeneity and measurement error, and Johnston and Sarbahi (2016) both found that decapitation reduces violence. Most recently, Rigterink (2021) found a causal blowback effect.

Our instrumental variables analysis, using 2SLS, suggests that decapitating drone strikes increase suicide bombings (Table 2.6), that is, we agree with Rigterink (2021) using a completely different identification approach. The magnitude of our estimated drone-strike coefficient 2.80 is significantly larger than our estimated coefficients for all drone strikes, although statistical significance is only at the 10% level. Diagnostic tests support the endogeneity of decapitation strikes and the strength of our instruments.

Table 2.6 Instrumental Variable Regressions (Decapitation Effect)

	Dependent Variable: Number of Suicide Bombings
Variables	**2SLS with Newey-West S.E.**
Leader Killed in Drone Strike	2.80* (0.06)
Other Control Variables	Yes
Time Dummies	Yes
1st Stage F stat	8.45
Montiel-Pflueger Effective F Statistic	9.72
Endogeneity Test *Null Hypothesis= Variables are Exogenous*	6.23 (0.01)
Wald chi2	43.07
Prob>Chi2	0.00
No. of Obs	441

Constant included in the model. Parentheses contain p values. **** p< 0.01, ** p< 0.05 and * p<0.10.*

2.5.3 Spatial Distribution Effects

All of the above results concern suicide attacks at the national level. We now distinguish between four different areas at increasingly large distances from North Waziristan (Table 2.7).[24] The estimates suggest that most of the first-week suicide-bombing reaction to drone strikes occurs between 100 and 300 kilometers from North Waziristan.[25]

[24] We add a spatial lag on suicide bombing to our usual set of controls for these estimates in keeping with their spatial emphasis.
[25] We do not report results for models for regions beyond 400 km as they are quite small.

Table 2.7 Spatial Allocation Effect

Variables	Dependent Variable: Number of Suicide Bombings			
	Between 0-100 KM from NW	**Between 100-200 KM from NW**	**Between 200-300 KM from NW**	**Between 300-400 KM from NW**
Drone Strike	0.086* (0.09)	0.169** (0.04)	0.165** (0.01)	0.026 (0.37)
Other Control Variables	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
F stat	2.65	4.75	2.93	2.21
Prob>F	0.000	0.000	0.000	0.000
No. of Obs	441	441	441	441

Constant included in all models. Parentheses contain p values. **** p< 0.01, ** p< 0.05 and * p<0.10.*

Table 2.8 repeats the analysis of Table 2.7 but with time counted in four-week intervals. The findings from predicted spatial allocation effects are reported in Table 2.9. Again, we find that most of the suicide-bombing response to drone strikes comes within a 100 to 300 kilometer range of North Waziristan.

Table 2.8 Follow-up Spatial Allocation Effect

Variables	Dependent Variable Number of Suicide Bombings In period t+ 4 weeks			
	Between 0-100 KM from NW	**Between 100-200 KM from NW**	**Between 200-300 KM from NW**	**Between 300-400 KM from NW**
Drone Strike	0.291* (0.06)	0.762** (0.01)	0.638*** (0.00)	0.031 (0.77)
Other Control Variables	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
F Stat	4.82	8.21	3.99	3.13
Prob>F Stat	0.000	0.000	0.000	0.000
No. of Obs	438	438	438	438

Constant included in all models. Parentheses contain p values. **** p< 0.01, ** p< 0.05 and * p<0.10.*

Next, we investigate whether suicide-bombing responses to drone strikes really do dissipate after 400 kilometers from North Waziristan as Tables 2.7 and 2.8 seem to suggest. Table 2.9 addresses this issue by repeating 2SLS estimates in Tables 2.2 and 2.5 but considering suicide bombings only within a 400-kilometer radius of North Waziristan. The estimated coefficients of 0.45 and 1.49 are close to the earlier estimated coefficients of 0.38 and 1.45, suggesting that, indeed, the reaction dissipates by the 400-kilometer mark.

Table 2.9 Subsample of 0-400 km from N.W

	Week-Level Contemporaneous Impact	**Follow-up Impact**
Variables	**Dependent Variable Number of Suicide Bombings**	**Dependent Variable Number of Suicide Bombing In period t+4 weeks**
Drone Strike	0.445 (0.00)	1.49 (0.00)
Other Control Variables	Yes	Yes
Time Dummies	Yes	Yes
F	8.34	18.69
Prob> F	0.00	0.00
No. of Obs	441	441

Constant included in all models. Parentheses contain p values. **** p< 0.01, ** p< 0.05 and * p<0.10.*

2.6 Further Robustness Checks

We ran bivariate probit regression where the dependent variable is 1 if there is a suicide attack within the week after a drone strike and 0 otherwise. Again, we get a large and statistically significant effect of drone strikes on suicide attacks (Table 2.10).

Table 2.10 Bivariate Probit Regression

Variables	**Dependent Variable Number of Suicide Attacks**
Drone Strike	0.725** (0.02)
Other Control Variables	Yes
Time Dummies	Yes
LR Chi2	149.92
Prob>Chi2	0
No. of Obs	441

Constant included in all models. Parentheses contain p values. **** p< 0.01, ** p< 0.05 and * p<0.10.*

Next, Appendix 2 reports estimates from a Three-Stage Least Squares (3SLS) estimator (Table AP2-2), which is more efficient than 2SLS and is also preferred if errors across equations are correlated (Cameron and Trivedi, 2009). The results turn out to be quite similar to the 2SLS estimates. Finally, Table AP2-3 reports estimates using casualties in drone strikes rather than drone-strike events to explain deaths in suicide bombings. Again, we find large and statistically significant effects that are supported by diagnostic tests.

2.7 Discussion

We find that drone strikes cause substantial increases in suicide bombing. These results are in conflict with theoretical propositions and empirical findings in Johnston & Sarbahi (2016), Mir and Moore (2018), Byman (2013), and Horowitz, Kreps, and Fuhrmann (2016). However, none of these works grapple seriously with the endogeneity issue. Both Mahmood and Jetter (2019) and Rigterink (2021) do, in very different ways, and find that drone strikes cause terrorism.

In contrast to all studies mentioned above, we specifically focus on suicide bombing. When we use an OLS estimator to measure the parameters instead, the coefficient of drone strikes turns out to be negative with weak statistical significance [see Appendix V]. This would imply, as most of the previous studies have found as well, that drone strikes deter suicide bombing. However, various diagnostic tests reported earlier provide evidence in support of the endogeneity of drone strikes and the use of instruments. This is true even when we use alternative specifications and estimators such as Bivariate Probit and 3SLS. Hence, the results from OLS estimation are biased and not reliable. Also, it is not without precedent to have opposite signs in estimates from OLS and IV regression. An influential paper by Levitt (1997) on the effect of police on crime is one example.

There are two major findings from empirical analysis. First, an increase in drone strikes leads to around 0.372-0.453 increase in suicide bombing. There is also evidence for at least 1 suicide bombing within a month following drone strikes. Possible blowback mechanisms are an increase in recruitment, perhaps including relatives of civilians killed in drone strikes, and retaliation. Shah (2018) uses an opinion poll to argue against the notion that drone strikes stimulate the recruitment of militants documented opinions of residents of tribal areas. However, his sample is biased towards strata of society targeted by the Taliban and there are documented stories about individuals resorting to suicide bombings to avenge deaths of relatives in drone strikes. For example, one Pakistani reported that “My neighbor was so furious when a drone killed his mother, two sisters, and his 7-year-old brother last September that he filled his car with explosives and rammed it into a Pakistani army convoy. He had to avenge the death of his loved ones”.[26] Tehrik Taliban Pakistan (TTP) has also claimed many attacks, such as the one in March 2009 in Lahore against the police academy, as retaliation for a drone strike.[27] Feffer (2016) suggests, correctly in our view, that blowback can happen without a substantial fraction of the population turning to violence in response to drone strikes and without a general consensus that drone strikes are bad. Strong reactions from a small minority of the population are sufficient, especially if these reactions involve suicide bombings which cause roughly 13 deaths and 43 injuries per attack. The strengthened reactions we find to such drone strikes that eliminate militants' leaders seem more likely to be driven by retaliation since such strikes seem unlikely to particularly affect recruitment. However, Rigterink (2021) argues that the best explanation involves splintering and infighting within terrorist groups that leads to indiscipline after leaders are killed.

The spatial allocation analysis suggests that all of the impact is exhausted within a 0-400 km radius from North Waziristan. This radius covers almost all of Khyber Pakhtunkhwa (KPK) province, the capital city of Islamabad, major cities within Punjab province such as Rawalpindi, Faisalabad, Multan, and the periphery of Lahore. Saeed, Syed, and Martin (2014) studied patterns in militancy in Pakistan and found that a large fraction of the violence during the 2000s took place in KPK and the erstwhile FATA regions, primarily because it was the latter region that was the launching pad for insurgency in Pakistan. The interior Sindh and major parts of Baluchistan seem to be almost immune from suicide bombings in retaliation for drone strikes.

[26] Cited in Williams (2010).
[27] See in BBC's report http://news.bbc.co.uk/1/hi/world/south_asia/7973540.stm.

2.8 Conclusion

Our findings suggest that drone strikes in Pakistan are counterproductive. We did only include strikes in North Waziristan, but these account for around 70 percent of all drone strikes in Pakistan carried out by the CIA. Our main contribution is to use cloud cover, precipitation, and a dummy for US drone base closure in Pakistan to instrument for drone strikes, thereby addressing an endogeneity problem that has plagued part of the literature in this area. Diagnostic tests support both the existence of the endogeneity problem and the quality of our instruments. The results indicate that drone strikes result, on average, in at least 1 suicide bombing in the subsequent month. These results suggest that roughly 27-33 percent of the suicide bombings occurring between July 2008 and the end of 2016 can be attributed to drone strikes. The impacts are strongest between 100 and 300 kilometers from drone strike locations with no statistically significant impact beyond a 400-kilometer radius. The results also indicate particularly strong reactions to drone strikes that eliminate militants' leadership. These findings are robust to different estimators and specifications, including LIML, 2SLS, 3SLS, GMM, and Bivariate estimations. There is now a growing body of evidence pointing to the counterproductive nature of drone strikes.

Appendix 2

Table AP2-1 Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
No. of Drone Strikes	0.672	1.18	0	7
No. Killed in Drone Strikes	4.595	8.41	0	50
No. of Leaders Killed in Drone Strikes	0.102	0.400	0	3
No. of Suicide Bombings	0.921	1.13	0	6
No. Killed in Suicide Bombings	11.98	22.10	0	108
Cloud Cover (% of total sky)	11.70	9.24	0	46.29
Precipitation mm	0.391	0.721	0	5.71
Cloud Cover * Precipitation	59.24	154.80	0	1444.27
Drone Base Closure	0.600	0.491	0	1
Ramadan	0.104	0.306	0	1
Muharram	0.090	0.287	0	1
Elections	0.023	0.149	0	1
Zarb e Azab	0.301	0.459	0	1
Rah e Haq	0.075	0.263	0	1
Rah e Rast	0.023	0.149	0	1

TableAP2-2 Instrumental Variable Regression with 3SLS

Dependent Variable: No. of Suicide Bombings

Variables	Total Sample	0-100 KM	100-200 KM	200-300 KM	300-400 KM
Drone Strikes	0.443*** (0.00)	0.112* (0.05)	0.255*** (0.00)	0.221*** (0.00)	0.023 (0.41)
Other Control Variables	Yes	Yes	Yes	Yes	Yes

Constant included in all models. Parentheses contain p values. **** p< 0.01, ** p< 0.05 and * p<0.10.*

Table AP2-3 Instrumental Variable Regression

Dependent Variable: No. of Suicide Bombings

Variables	2SLS with Newey-West S.E.
No. of Fatalities in Drone Strikes	1.49 (0.00)
Other Control Variables	Yes
Time Dummies	Yes
Root MSE	23.62
1st Stage F stat	38.39
Montiel-Pflueger Effective F Statistic	42.54
Endogeneity Test *Null Hypothesis= Variables are Exogenous*	9.73 (0.00)
Wald chi2	36.72
Prob>Chi2	0.00
No. of Obs	441

Constant included in all models. Parentheses contain p values. **** p< 0.01, ** p< 0.05 and * p<0.10.*

Chapter 3
Estimating the Impact of Military Expenditure on Economic Growth: A New Instrumental Variables Approach

3.1 INTRODUCTION

I examine the impact of military expenditures on economic growth and propose a new identification strategy for tackling the endogeneity of military expenditures in the growth model. The empirical findings on whether military expenditures stimulate (by increasing employment opportunities, transfer of military technology to civilian industry, etc.) or retard economic growth (for instance by crowding out productive investment) are mixed (Dunne & Tian, 2013). This heterogeneity in findings is mainly attributed to differences in samples and model specifications (Aziz & Asadullah, 2017) but more importantly to the endogeneity of military expenditures variable in the growth model (Smith, 2017; d'Agostino, Dunne, & Pieroni, 2019). The potential sources of this endogeneity problem are manifold. For instance, economic growth can exert a reverse caa usual impact on military expenditures as higher growth makes additional resources available for a defense buildup. Also, as I discuss in detail in the *Empirical Strategy* section, both economic growth and military expenditure variables are likely to be affected by common unobserved factors (d'Agostino, Dunne, & Pieroni, 2019). As a result, the estimates from the growth models which do not account for the endogeneity of military expenditures can be biased.

I propose two new instruments for military expenditure variable in the growth model: arms imports during peace time (when yearly battle-related deaths are below 25) and the number of neighboring states suffering interstate violence. I illustrate in detail in the section *Empirical Strategy* that the effects of these two instruments on economic growth are likely to channelize through their impact on the military expenditures variable. The results from several diagnostic tests provide supporting evidence that both these instruments are highly correlated with the military expenditures variable and satisfy overidentification restrictions.

The regression analysis exploits panel data on 133 countries covering the period of 1960-2012. The results from IV regressions suggest that a 1 percentage point increase in military expenditures as a percentage of GDP leads to approximately a 1.10 percentage points reduction in economic growth. This estimate of -1.10 is significantly larger in magnitude than the estimate of -0.281 obtained from a fixed effect model which includes military expenditures as an exogenous variable. The statistically significant negative effect of military expenditure on economic growth is also observed in samples of developing, conflict-affected, and below than average human rights performing countries.

The empirical literature on the impact of military spending on economic growth abounds. Several literature reviews already exist which provide insightful overviews of the trends in the findings from the studies published over the past four decades (Chan, 1987; Ram, 1995; Dunne, Smith and Willenbockel 2005; Smaldone, 2006, Dunne & Tian, 2013). Therefore, I restrict myself to a very brief discussion of the literature. Theoretical and empirical works of Clive Trebilcock and Emile Benoit during the 1970s initiated a serious debate on the utility of the defense sector for economic development. Their work was followed by a plethora of studies that employed econometric methodologies to analyze case studies, (Chan, 1988; Antonakis, 1997; DeRouen, 2000; Phiri, 2019; Ahmed, Khorshed, Rashid, & Gow, 2020) and n sample studies (Cappelen & Bjerkholt, 1984; Dunne & Mohammad, 1995; Landau, 1996; Blomberg, 1996; Stroup & Heckelman, 2001; Aizenman & Glick, 2006; Kollias, Mylonidis, & Suzanna-Maria, 2007; Yakovlev, 2007; Karadam, Yildirim, & Ocal, 2016; Aziz & Asadullah, 2017). Table AP4.1 in Appendix I provides a summary of the main findings from these studies.

Empirical findings in this area have long been mixed, however, potentially due to the increasing availability of data in the post-Cold war period, a consistent pattern is unfolding in the findings which indicate the negative impact of military expenditures on growth (d'Agostino, Dunne, & Pieroni, 2019). Dunne and Uye (2009) observed in a survey of 103 studies that only 20 studies showed a positive impact of military expenditure on growth/development. The negative impact was observed in 37 studies, whereas in the remaining 43 studies, the results were inconclusive.

However, the endogeneity problem remains a key concern in inferring about the causal impact of military expenditures on economic growth. The challenge is to identify instrument(s) which cause exogenous variations in military expenditures but not in the economic growth variable (Smith R. P., 2017; d'Agostino, Dunne, & Pieroni, 2019). While some studies, such as Chang, Huang, & Yang (2011), exploited pre-determined lag vales of military expenditures as instruments and employed Arellano and Bond (1991) estimator for estimation; to the best of my knowledge d'Agostino, Dunne, & Pieroni (2019) is the only study which employed excluded instrument obtained from outside of the data as an instrument for military expenditure d'Agostino, Dunne, & Pieronthe i, (2019) employ a dummy variable which captures transition from unrest to turmoil as an instrument for military expenditures. The threshold level for turmoil is set at a level where number of organized violent[1] events exceeds the mode of its distribution. The relevance of the instrument is based on the premise that it reflects the "political environment" that a country faces without capturing the *destruction produced by the related activities* (d'Agostino, Dunne, & Pieroni, 2019). The results from their empirical analysis of 109 non-high-income countries, covering a period of 1988-2012, suggest that the negative impact of military expenditure on economic growth is larger than the one indicated by the estimate from the OLS model. The size of the estimate increases from -0.629 in the OLS model to -2.791 in the IV model. The empirical strategy in d'Agostino, Dunne, & Pieroni, (2019) is certainly a valuable addition to the existing literature. However, their econometric model is "just identified" which implies that while correlation of the instrument with military expenditures can be examined, but whether the instrument is uncorrelated with the error term, i.e., $corr(Z_{it}, \mu_{it}) = 0$, remains untested.

[1] Any violent incident is classified as organized violence *where armed force was used by an organized actor against the government of an independent state resulting in at least one direct death at a specific location and a specific date* (d'Agostino, Dunne, & Pieroni, 2019)

As a step forward, I suggest two news instruments which allow testing of overidentification restrictions. In the next section, I outline empirical strategy and provide arguments in favour of the plausibility of these two instruments.

3.2 Empirical Strategy

I employ regression analysis to estimate the impact of military expenditures on economic growth. However, as discussed in the previous section, the issue of endogeneity remains a main concern.

Consider the following fixed-effect model,

$$GR = \beta_0 + \beta_1 ME/GDP_{it} + \beta_2 X_{it} + \delta_i + \mu_{it} \dots \dots \dots . eq1$$

Where GR= Growth Rate, ME/GDP= Military expenditure/ GDP, X= vector of control variables, δ =country-level fixed effects and μ= error term.

The coefficient of interest in this model is β_1. This coefficient can be biased for two reasons. First, there is a possible reverse causal impact of economic growth on military expenditures (d'Agostino, Dunne, & Pieroni, 2019).[2] Second, both economic growth and military expenditures variables are likely to be affected by unobserved common factors. It is not possible to quantify all such factors hence they are included in the error term. To some extent, the country level fixed effects δ, can capture time-invariant un-observables, such as geography, however other potential sources of influences on military expenditures and economic growth variables remain excluded from the model. For instance, in many developing countries, militaries exercise a strong influence on politics and the economy (Mani, 2007), and the degree of such influence cannot fully be quantified. Militaries can instrumentalize their influence to channel a larger share of a state's resources towards military expenses, while at the same time, through their involvement in the economy as owners of economic enterprises (Mani, 2007), exert direct influence on economic growth. If the true $\beta_1 < 0$ then omitting the military influence variable,

[2] d'Agostino, Dunne, & Pieroni, (2019) provide a mathematical illustration of the reverse causal impact of economic growth on military expenditure.

which is likely to positively correlate with the military expenditure variable, can cause downward bias in β_1. There can be other factors that affect $\beta_1$in a similar manner.

To account for this possible bias in β_1, I propose an instrumental variables approach in which I use 1) the value of arms imports during peace time and 2) the number of neighboring states suffering interstate violence as instruments for the military expenditures variable. These two variables are likely to affect economic growth indirectly through their impacts on military expenditures.

Consider the case of the value of arms imports during peace time first. In many cases, the purchase orders for these arms are placed several years before the year they are delivered to the recipient countries. For instance, Algeria placed an order for TPS-70 air search radars with the US in 1998 which were delivered in 2000. Bolivia received Star-NG air search radars from the UK in 2019 following a purchase deal settled in 2016. Burundi ordered Armoured Personnel Carriers (APC) from the US in 2014 which were delivered in 2015.[3] Because of this time lag between the placement of purchase orders and delivery of weapons, it can be safely assumed that economic growth in year t is unlikely to have any effect on arms imports in year t.[4] Also, in the case of developing countries, which dominate the sample, procurement of military aid plays a major role in enabling the purchase of these weapons rather than internal resources.[5]

It could be argued that at least some fraction of the arms which flow to the recipient country, might be launched in combat in an internal conflict during the same year and therefore may exert a direct impact on economic growth through the destruction of capital. To mitigate some of this effect, I use the value of arms imports during peace time. Uppsala Conflict Database Program (UCPD) defines conflict as ongoing if the yearly battle-related deaths cross a threshold of 25 (Kreutz, 2010). In line with this definition, I define peace time as a year when the battle-related deaths are less than 25.

[3] This information is taken from the Arms Flow Trade Registers database of Stockholm International Peace Research Institute (SIPRI) (Stockholm International Peace Research Institute, 2021). Web link- https://sipri.org/databases/armstransfers

[4] In a linear regression of arms flow during the period of no active conflict, the estimated coefficient for GDP per capita on the growth rate is statistically insignificant.

[5] See detailed trade registers of SIPRI's arms transfer database Stockholm International Peace Research Institute, (2021). The information on whether military aid financed the procurement of weapons can be found in the comment section of the trade registers.

The frequency of neighboring states suffering interstate violence captures the atmosphere of regional political uncertainty which positively correlates with military spending. Table 3.1 shows a positive correlation between average military expenditure/ GDP with different levels of frequencies of neighboring states suffering interstate violence.[6].

Table 3.1 Average Military Expenditures and Number of Neighboring States with Interstate Violence

Number of Neighbouring States with Interstate Violence	Frequency (Country-Years)	Mean Military Expenditure / GDP
0	7621	2.66
1	861	4.76
2	199	5.58
3	40	9.16
4	6	4.29+

The data for military expenditure/ GDP is taken from Stockholm International Peace Research Institute (SIPRI). Information on the number of neighboring states with interstate violence is taken from Major Episodes of Political Violence Database of Center for Systemic Peace (Center for Systemic Peace, 2019). + No. of observations for military/expenditure which correspond to 4 neighboring states with interstate violence is only 1.

A regional security environment can prompt countries to increase military spending as a preemptive measure (Moon & Lee, 2009). Phillips (2015) also found civil wars in the neighborhood reaching the borders of a country to lead to an increase in military spending. While the positive effect of such security challenges in neighboring countries on a country's military spending seems plausible, to serve as a valid instrument in the present context, it should not directly affect a country's economic growth. In this connection, it is worth mentioning here are the findings from Murdoch & Sandler (2004) which show no statistically significant negative impact of civil wars in neighboring states sharing continuous border on a country's both short-run and long-run economic growths.[7] Not only have civil conflicts

[6] The only exception is for average military expenditure/ GDP which corresponds to 4 neighboring states with interstate violence. This estimate is unreliable because the number of observations for military expenditure/ GDP which corresponds to 4 neighboring states with interstate violence is only 1

[7] However, they do observe the negative effect of civil wars in countries within 800 km distance on economic growth.

dominated global armed conflict trends in the post-second world war period but also the number of deaths in these conflicts has been higher than in the interstate wars during the same period.[8] Being less deadlier than intrastate conflicts during the period covered in this study hence causing lesser destruction, it can be safely assumed that, like intrastate conflict, interstate warfare in neighboring contiguous states is unlikely to have any significant direct effect on a country's growth rate. To further support this idea with empirical evidence, I also estimate auxiliary regressions for growth rate, which I discuss in the next section, to show that the effect of neighboring states suffering interstate violence on growth rate is channelized through its effect on the country's military spending [see Table 3.4].[9]

To account for the endogeneity of military expenditures by using arms imports during peace time and the number of neighboring states with interstate violence as instruments, I propose the following two-stage model. The first equation is the model for military expenditure/ GDP whereas the second equation is an endogenous growth model which includes military expenditure/ GDP as an endogenous covariate.

$$\frac{ME}{GDP} = \alpha_0 + \alpha_1 ARMSIMPORTS_{it} + \alpha_2 NINT_{it-1} + \alpha_3 X_{it} + \gamma_i + \varepsilon_{it} \ldots\ldots\ldots. eq2$$

$$GR = \emptyset_0 + \emptyset_1 Pr.ME/GDP_{it} + \emptyset_2 X_{it} + \vartheta_i + \in_{it} \ldots\ldots\ldots. eq3$$

Where ARMSIMPORTS= Value of arms during peace time, NINT= No. of neighboring states with interstate violence,γ & ϑ= Country-level fixed effects and ε & $\in$= error terms.

[8] For instance, during 1990-2002 period, civil conflicts were responsible for 90 percent of deaths in violent conflicts (Lacina, 2006). Research reported on Stanford University's website also shows that during 1945-2002 period 16.5 million people died in civil wars as compared with 3.3 million in interstate wars. For more see Causes of world's civil wars misunderstood, researchers say: 9/02 (stanford.edu)

[9] Based on Murdoch & Sandler (2004) findings I also employ number of neighbouring states suffering civil violence as instruments for military spending but I observed stronger econometric support for interstate violence variable as an instrument.

For robust inferences, I employ Two-Stage Least Square (2SLS), Limited Information Maximum Likelihood (LIML) and Generalized Method of Moments (GMM) estimators to estimate this system of equations. While 2SLS is widely applied and understood, LIML performs better if instruments are weak whereas GMM is suitable for overidentified models (Cameron & Trivedi, 2009)

3.3 Data Source

3.3.1 Dependent Variable: GDP Per Capita Growth Rate

The main dependent variable is the GDP per capita growth rate. The data for this variable is taken from the World Development Indicators (WDI) database of the World Bank (The World Bank, 2021).

3.3.2 Instrumented variable: Military Expenditure / GDP

Military expenditure is the explanatory variable of interest. It is normalized with the total GDP to reflect a country's military burden. The data for this variable is taken from Stockholm International Peace Research Institute (SIPRI) data (Stockholm International Peace Research Institute, 2021).

3.3.3 Instrumental Variables

3.3.3.1 Value of Arms Imports

Value of arms imports during peace time is used as an instrument for military expenditure. The data for the value of arms imports is taken from Stock International Peace Research Institute (SIPRI) database. This variable is then interacted with a dummy for peace time which assumes a value of 1 for country-year when battle-related deaths are less than 25.

SIPRI provides data on what it describes as Trend Indictor Value (TIV) of arms imports- a common unit that enables a comparison of the value of arms imports across countries and years. TIV is measured based on the unit cost of production of weapons and therefore does not exactly represent prices at which these arms are sold. For this reason, TIV cannot fully capture the actual burden of arms imports in military expenditure. However, this does not pose any serious difficulty for the present analysis since the objective here is not to estimate such a burden of arms imports but rather to identify exogenous variations in military expenditures that TIV is likely to cause. Despite that TIV is valued at cost of production of arms, not at their sales prices, economic logic suggests that it positively correlates with military expenditures because military items which are produced dearly are likely to be sold at higher prices. In the next section, I examine the relationship between the value of arms imports and military expenditures using graphs and regression analysis.

3.3.3.2 Number of Neighboring States with Interstate Violence

This variable captures the frequency of neighboring states with interstate violence. Neighboring states are those with which a state shares a contiguous border or a water border of two miles width or less.[10] The data for this variable is taken from the Major Episodes of Political Violence Database of the Center for Systemic Peace (Center for Systemic Peace, 2019). I include this variable in the model with a single lag as its effect on military spending is likely to take some time to unfold

3.3.4 Other Control Variables

I also control for additional explanatory variables which include, lagged growth rate, non-military expenditure/GDP, gross fixed capital formation/ GDP, trade openness measured as the sum of imports and exports/ GDP, ethnic fractionalization index, log of the total population, inflation, and life expectancy. The non-military expenditure/ GDP variable is constructed by subtracting military expenditure/GDP from current government spending/ GDP. Given the budget constraint that any government faces, any variation in military expenditure/ GDP will also cause changes in non-military expenditure/GDP and if the latter variable is dropped, then the model can suffer from omitted variable bias (d'Agostino, Dunne, & Pieroni, 2019). The data for current government spending/ GDP is taken from the World Development Indicators (WDI) database of the World Bank. The data for gross capital formation/GDP and imports and exports as a percentage of GDP is also taken from the World Development Indicators (WDI) of the World Bank. Ethnic fractionalization measures the probability of

[10] A complete list of neighboring states for each state is provided in the annex. 2 of Major Episodes of Political Violence codebook at http://www.systemicpeace.org/inscr/MEPVcodebook2018.pdf.

two randomly selected individuals not being from the same ethnic group. The data for this variable is taken from (Drazanova, 2019). Total population, inflation, and life expectancy data are collected from the World Development Indicators (WDI) database of the World Bank. I also include dummies for several important global events such as the Iran-Iraq war (1980-88), the First Gulf War (1990-91), the post-cold war period (1991-to date), the financial crisis of 2008-09, and the economic recession of 1974-75 which affected several western countries following the Oil Price Shock of 1973.

The total sample consists of 133 countries covering the period of 1960-2012. In all the models, I estimate Driscoll & Kraay (1998) standard errors which are robust to heteroscedasticity, autocorrelation as well as cross-sectional dependency. Descriptive statistics on these variables are reported in Table 3.2. Over the sample period of 1960-2012, the average military spending was 2.89 percent of GDP but during the outbreak of hostilities military expenditures significantly increased from this average. For instance, in 1973 due to the war with a coalition of Arab states, Israel's military spending increased to around 28 percent of its GDP. Kuwait's military expenditure stood at an incredible 117 percent of its GDP during the 1991 Gulf War.

Table 3.2 Descriptive Statistics

Variables	Observations	Mean	Std. Dev.	Min	Max
GDP Per Capita Growth Rate	7,377	2.18	6.35	-64.99	140.37
Military Expenditure/ GDP	6,045	2.89	3.46	0.00	117.35
Non-Military Expenditure/ GDP	5,231	12.92	6.22	0.38	114.86
Intensity of Violence	10,229	0.18	0.48	0.00	2.00
Life Expectancy	9,333	62.61	11.65	18.91	83.48
Ethnic Fractionalization	7,299	0.44	0.27	0.00	0.89
Log of Total Population	9,635	15.29	1.98	9.19	21.02
Inflation	6,274	22.28	216.02	-18.11	11749.60
Trade Openness	6869	73.83	49.19	0.02	437.32
Gross Fixed Capital/GDP[11]	6473	22.76	8.83	-13.40	95.32

[11] This variable can assume a negative value because the World Development Indicators (WDI) database of the World Bank calculates it by using the value of additions to the fixed assets net of inventories.

3.4 Empirical Results

Figure 3.1 plots mean values for both instruments, i.e., the value of arms imports during peace time and the number of neighboring states with interstate violence, and military expenditures. Both instruments appear to positively correlate with military expenditure.

The strengths and statistical signi of these correlations can be examined using regression analysis. Table 3.3 presents regression results for the first stage military expenditure model (eq 1). The estimated coefficients for both arms imports during peace time and the number of neighboring states with interstate violence are positive and statistically significant showing their strong correlations with military expenditure.

Figure 3.1 Trends in Military Expenditure/ GDP, Value of Arms Flow During Peace Time & No. of Neighboring States with Interstate Violence

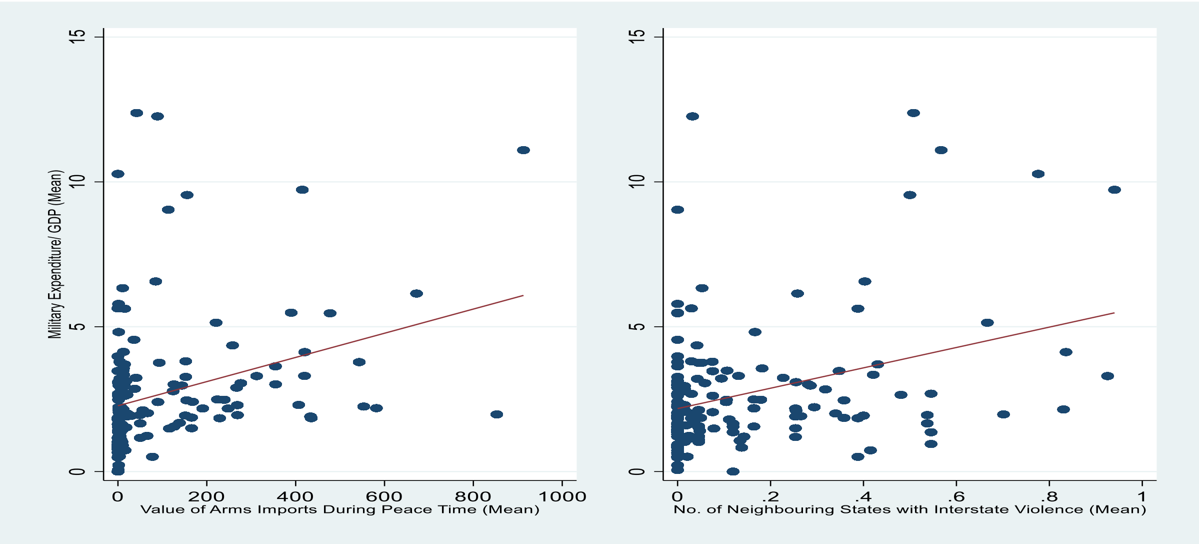

Table 3.3 Results for Military Expenditure Model

Dependent Variable: Military Expenditure/ GDP

	Model 3.3.1
Variables	**Fixed Effect**
Arms Flow During Peace Time	0.0002*** (0.00)
No. of Neighboring States with Interstate Violence	0.110** (0.03)
Other Controls	Yes
Country Fixed Effects	Yes
Years-Fixed Effects	Yes
Prob > F	0.00
Within R^2	0.77
Observations	4169

*Constant included in the model. Other controls include lagged military spending, GDP per capita growth rate, logged GDP per capita, logged population, ethnic fractionalization, life expectancy, non-military spending, trade openness and intensity of conflict. Parentheses contain p values where *** p< 0.01, ** p< 0.05 and * p<0.10. Driscoll Kraay standard errors are estimated in all models.*

Now I turn to the presentation of results for economic growth models. The results from non-IV fixed effect models are reported in Table 3.4. The coefficient for military expenditure is negative and statistically significant at 5 percent. In Model 3.4.2, I drop the military expenditures variable and estimate the direct effect of both instruments on economic growth which turns out to be statistically significant. However, once I control for military expenditures along with the instruments in Model 3.4.3, the statistically significant effect of both instruments on economic growth disappears which lends support to the idea that both instruments affect economic growth indirectly through their effects on military expenditures.

The results from the second-stage model (eq2) are reported in Table 3.5.[12] As stated above, for robust inference I estimate models using 2SLS, LIML, and GMM estimators. The size of the coefficient for military expenditures variable in Model 3.5.1 increases substantially in size to -1.10, which is approximately 3.91 times larger in magnitude than the coefficient in the fixed effect model (-1.10/-0.281= 3.91) The statistical significance also improves as the coefficient in Model 3.5.1 has a p value of less than 1 percent. Model 3.5.2 is estimated using the LIML estimator. The size of the coefficient changes marginally to -1.11 and remains statistically significant at 1 percent. To estimate Model 3.5.3, I employ a GMM estimator. The size of the coefficient is -1.11 and it is statistically significant at 1 percent. The size of standard errors in the three models changes by a very small magnitude.

Table 3.4 Results for Economic Growth Models (Non- IV/Full Sample)

	Model 3.4.1	**Model 3.4.2**	**Model 3.4.3**
	Fixed Effect	**Fixed Effect**	**Fixed Effect**
Military Expenditure/ GDP	-0.281*** (0.05) [0.070]		-0.251*** (0.00) [0.066]
No. of neighboring states suffering interstate violence$_{t-1}$		-0.608 (0.05) [0.311]	-0.501 (0.11) [0.310]
Arms flow during peace time		0.001 (0.04) [0.0003]	-0.001 (0.13) [0.0003]
Other Control Variables	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes

[12] In the main text I maintain focus on the interpretation of the results for military expenditures variables. The full set of results are reported in Table AP3.2 in the Appendix.

With R^2	0.15	0.14	0.15
Prob > F	0.00	0.00	0.00)
Observations	3985	3968	3968

*Constant included in the model. Parentheses contain p-value whereas brackets contain Driscoll Kraay standard errors. *** p< 0.01, ** p< 0.05 and * p<0.10.*

Table 3.5 Results for Economic Growth Models (IV/Full Sample)

	Model 3.5.1	**Model 3.5.2**	**Model 3.5.3**
	2SLS	**LIML**	**GMM**
Military Expenditure/ GDP	-1.10*** (0.00) [0.413]	-1.11*** (0.00) [0.416]	-1.11*** (0.00) [0.412]
Other Control Variables	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Prob > F	0.00	0.00	0.00
Observations	3966	3966	3966

*Constant included in the model. Parentheses contain p-value whereas brackets contain Driscoll Kraay standard errors. *** p< 0.01, ** p< 0.05 and * p<0.10.*

3.4.1 Diagnostic Tests

The plausibility of these results depends upon the relevance, validity, and strength of the instruments used for the military expenditure variable. I employ several diagnostic tests to determine whether arms flow during peace time and the number of neighboring states with interstate violence serve as good instruments for military expenditure variable. But before that, I first conduct an endogeneity test[13] to empirically examine whether it is appropriate to treat military expenditures as an endogenous covariate [see Table 3.6]. If it is not, then there is no sound empirical justification for ignoring the estimate from the FE model (Model 3.4.1) The result shows that the null hypothesis that military expenditure can be treated as exogenous is rejected with a p-value of 0.03. This provides statistical evidence in favor of modeling military expenditures as an endogenous covariate in the growth model.

Table 3.6 Diagnostic Tests

Endogeneity Test- p-value Ho: ME/GDP is exogenous	0.03
Under-identification test (Kleibergen-Paap rk LM statistic) H0: Equation is under-identified	0.00
F Stat of Excluded Instrument Prob> F	18.16 (0.00)
Weak Instruments Test Montiel Pflueger Effective F Statistic H0: Bias in the estimator exceeds percentage τ of worst-case bias	22.79 α=0.01 2SLS
5 % of worst-case bias	13.04
Hansen J Statistic- p-value Ho: Instruments are valid	0.62
Instrument Redundancy Test p-value	
Ho: Arms transfer is redundant	0.01
Ho: Number of neighboring states with interstate violence	0.02

Then I test for under-identification[14] i.e., whether the excluded instruments are relevant and correlate with endogenous variable military expenditure. The null hypothesis that the model is under-identified is rejected with a p-value of less than 1 percent. While the results for under-identification suggest that

[13] This test is implemented in Stata using the XTIVREG2 command. It is based on a difference of Sargan-Hansen statistics for the equation in which the suspected covariate is treated as endogenous and controls include a smaller set of instruments and for the equation in which the suspected covariate is treated as an exogenous and larger set of instruments are included.

[14] The statistic for this test is produced by the Stata command XTIVREG2. This is a test for the rank of a coefficients' matrix where rejection of the null hypothesis indicates that the matrix is full column rank.

instruments are relevant, the IV estimates can be biased if the instruments are only weakly correlated with the military expenditure variable. First, I estimate the joint statistical significance of excluded instruments. The rule of thumb is that relatively strong instruments should have an F statistic greater than 10 (Staiger & Stock, 1997) The estimated F Statistic for excluded instruments is 18.16.

Then, I employ the Montiel Olea & Pflueger (2013) weak instrument test which is robust to both heteroscedasticity and autocorrelation. The "effective F statistic" of Montiel Olea & Pflueger (2013) tests the null hypothesis of whether the asymptotic bias of an IV estimator exceeds a fraction τ of worst-case bias which will arise if the instruments are completely irrelevant. The null hypothesis that the bias from 2SLS exceeds 5 percent of worst-case bias is rejected at a 1 percent level of significance. Based on the rejection of the null hypothesis at such a low level of significance, it can be safely assumed that if there is any bias at all in the estimate, it does not exceed 5 percent of the worst-case bias. In other words, there is a very low probability for the estimate to be plagued by even a small fraction of 5 percent of worst-case bias.

Then I employ the Hansen J test to test whether overidentification restrictions are met. The null hypothesis that instruments are uncorrelated with the errors is rejected with a p-value of 0.62. Finally, I also test for whether either of the instruments is redundant where the null hypothesis is rejected in all cases. All the results from diagnostic tests provide strong evidence in favor of modeling military expenditures as an endogenous covariate in the growth model and, also on the appropriateness of using arms flow during peace time and the number of neighboring states with interstate violence as instruments for military expenditures. Together, these results provide evidence to assume that the estimate from FE Model 4.3.1 is biased and underestimates the effect of military expenditures on economic growth.

3.4.2 Controlling Heterogeneity in the Sample

To account for heterogeneity in the sample, I divide the full samples into 1) developing countries[15] 2) conflict-affected countries and those with 3) below average human rights performers sub-samples.

[15] Countries' classification is based on the United Nations criteria. See annexure to *World Economic Situations*

Several studies have observed that the impact of military expenditure on growth can vary with respect to the political and economic conditions of countries (d'Agostino, Dunne, & Pieroni, 2019; Dunne & Tian 2013)

Table 3.7 reports results from developing countries' sample. The size of the coefficient for military expenditure is -1.14 and has a p-value of less than 1 percent. There is no significant change in coefficient in Model 3.7.2 which is estimated using LIML estimator. The coefficient increases in size to -1.26 in Model 3.7.3 which is estimated using a GMM estimator. This coefficient in Model 3.7.3 is more reliable as it has a relatively smaller standard error and which shows quite a strong impact. For instance, if military expenditure in developing countries goes up by magnitude equivalent to 1 standard deviation (3.66), the economic growth reduces by 4.61 percent. In all these models, the results from the diagnostics test suggest that instruments are valid, strong, and fulfill overidentification restrictions. There are no significant differences in the coefficients from full sample and developing sample models which suggest that the negative impact of military expenditure on economic growth is mainly transmitted by the developing countries.[16]

Table 3.7 Results for Economic Growth Models (Developing Countries)

	Model 3.7.1	**Model 3.7.2**	**Model 3.7.3**
	2SLS	**LIML**	**GMM**
Military Expenditure/ GDP	-1.14*** (0.00) [0.393]	-1.11*** (0.00) [0.373]	-1.26** (0.03) [0.326]
Other Control Variables	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes

and Prospects (WESP) prepared by the y the Development Policy and Analysis Division (DPAD) of the Department of Economic and Social Affairs of the United Nations Secretariat (UN/DESA). https://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf

[16] In the developed country sample, the estimated coefficient for military expenditure/GDP in the fixed effect model is -0.122 model and has a p-value of 0.44.

Time Dummies	Yes	Yes	Yes
F Stat Prob > F	0.00	7.66 (0.00)	7.62 (0.00)
Under-identification test (Kleibergen-Paap rk LM statistic) H0: Equation is under-identified	0.01		
F Stat of Excluded Instrument Prob> F	17.04 (0.00)		
Weak Instruments Test Montiel Pflueger Effective F Statistic H0: Bias in the estimator exceeds percentage τ of worst-case bias	23.43 α=0.01 2SLS		
5 % of worst-case bias	12.27		
Hansen J Statistic Ho: Instruments are valid	0.98		
Endogeneity Test- p-value Ho: ME/GDP is exogenous	0.02		
Instrument Redundancy Test p-value Ho: Arms transfer is redundant Ho: Number of neighboring states with interstate violence	 0.001 0.0001		
Observations	2881	2881	2881

*Constant included in the model. Parentheses contain p-value whereas brackets contain Driscoll Kraay standard errors. *** p< 0.01, ** p< 0.05 and * p<0.10.*

Next, I restrict the sample to include countries that experienced conflict (more than 25 battle-related deaths) for at least 1 year. The size and statistical significance of the coefficients in Model 3.8.1-3.8.3 suggest that the negative impact of military expenditures on economic growth is consistent in conflict-affected countries.

Table 3.8 Results for Economic Growth Models (Conflict-Affected Countries)

	Model 3.8.1	**Model 3.8.2**	**Model 3.8.3**
	2SLS	**LIML**	**GMM**
Military Expenditure/ GDP	-0.999*** (0.00) [0.360]	-0.999*** (0.00) [0.360]	-0.976*** (0.00) [0.333]
Other Control Variables	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Prob > F	0.00	0.00	0.00
Under-identification test (Kleibergen-Paap rk LM statistic) H0: Equation is under-identified	0.01		
F Stat of Excluded Instrument Prob> F	15.64 (0.00)		
Weak Instruments Test Montiel Pflueger Effective F Statistic H0: Bias in the estimator exceeds percentage τ of worst-case bias	18.94 α=0.01 2SLS		
5 % of worst-case bias	12.96		
Hansen J Statistic Ho: Instruments are valid	0.87		
Endogeneity Test- p-value Ho: ME/GDP is exogenous	0.03		
Instrument Redundancy Test p-value Ho: Arms transfer is redundant Ho: Number of neighboring states with interstate violence	 0.01 0.02		

Observations	2620	2620	2620

*Constant included in the model. Parentheses contain p-value whereas brackets contain Driscoll Kraay standard errors. *** p< 0.01, ** p< 0.05 and * p<0.10.*
.

Finally, I restrict the sample to countries with below than average human rights performance. Human rights score is measured on an interval which represents a deviation from the global average set at 0- the lower the number the worse is the human rights situation (Fariss, 2019). I isolate a sample of countries that have human rights scores of less than 0 i.e., below average score. The strongest impact is observed in this sample of countries. The size of the coefficient is –1.33 in Model 3.9.3. If military expenditure/ GDP goes up by a magnitude equivalent 1 standard deviation in this sample, i.e., 3.77 percentage points, then economic growth reduces by 5.01 percentage points.

Table 3.9 Results for Economic Growth Models (Below Average Human Rights Performers)

	Model 3.9.1	**Model 3.9.2**	**Model 3.9.3**
	2SLS	**LIML**	**GMM**
Military Expenditure/ GDP	-1.34*** (0.00) [0.351]	-1.34*** (0.00) [0.352]	-1.33*** (0.00) [0.349]
Other Control Variables	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Prob > F	0.00	0.00	0.00
Under-identification test (Kleibergen-Paap rk LM statistic) H0: Equation is under-identified	0.004		
F Stat of Excluded Instrument Prob> F	26.21 (0.00)		

Weak Instruments Test Montiel Pflueger Effective F Statistic H0: Bias in the estimator exceeds percentage τ of worst-case bias	19.35 α=0.01 2SLS		
5 % of worst-case bias	11.50		
Hansen J Statistic Ho: Instruments are valid	0.67		
Endogeneity Test- p-value Ho: ME/GDP is exogenous	0.01		
Instrument Redundancy Test p-value Ho: Arms transfer is redundant Ho: Number of neighboring states with interstate violence	 0.02 0.005		
Observations	2077	2077	2077

*Constant included in the model. Parentheses contain p-value whereas brackets contain Driscoll Kraay standard errors. *** p< 0.01, ** p< 0.05 and * p<0.10.*

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3.5 Discussion and Conclusion

Despite that there is a substantial amount of literature that examines the impact of military expenditures on economic growth, there is no empirical consensus on whether the impact is positive or detrimental. While heterogeneity in the findings has been attributed to variations in samples and empirical methodologies, another key issue is that of endogeneity of military expenditures in the growth model. In a recent study- which to the best of my knowledge the only study which utilizes excluded instrument- d'Agostino, Dunne, & Pieroni, (2019) used a dummy that captures the transition from unrest to turmoil in a country as an instrument for military expenditures and isolated a larger negative impact of military expenditure on economic growth than the one suggested by the estimate obtained using OLS. However, overidentification restrictions could not be tested as the model in d'Agostino, Dunne, & Pieroni, (2019) is just identified.

This study employs the value of arms imports during period time and the number of neighboring states with interstate violence as instruments for military expenditures in the growth model. The results from IV regressions suggest that in developing countries, a 1 percentage point increase in military expenditure/ GDP decreases economic growth by approximately 1.26 percentage points. This is quite a strong impact if examined in terms of deviations. For instance, in developing countries, if military/expenditure goes up by 1 standard deviation (3.66)- roughly equivalent to the yearly average military burden of Myanmar, Morocco and Armenia- then economic growth reduces by 4.6 percentage points. An increase above the sample mean will cause a larger reduction in economic growth. For instance, on average developing countries spent 3.11 percent of their GDP on military spending during the 1960-2012 period. An increase in military expenditure/GDP of a magnitude equivalent to 1 standard deviation of the sample, i.e, 3.66, above the sample mean of 3.11, takes military spending to 6.67 percent of GDP- which is roughly equivalent to Jordan's average military spending during the 1990s. Such a high increase in military spending will reduce economic growth, even by the conservative estimate from Model 3.7.1, by 7.40 percentage points (6.67*-1.11=-7.40).

Unlike some of the previous findings in Landau, (1996), Stroup & Heckelman, (2001), and Karadam, Yildirim, & Ocal,(2016) I found no support for a U-shaped relationship between military spending and economic growth. The coefficient for squared military expenditure variables remains insignificant in all models.

The findings from the models support the perspective that the military burden can only be sustained at a significant cost to the economy. This cost is around a yearly 1.26 percentage point decrease in economic growth for a 1 percentage point increase in military expenditure/ GDP. These findings are robust to a variety of estimators employed for estimating the models.

Appendix 3

Table AP3.1 Brief Summary of Literature

Study	Coverage	Result
	Selected Case Studies	
Chan (1988)	Taiwan 1961-1985	Military expenditure reduces savings, investment, and infrastructural development
Antonakis (1997)	Greece – 1960-1990	Negative
DeRouen (2000)	Israel 1953-1992	Negative (Short term)
Phiri	South Africa 1988-2015	Inverted U shaped relationship
Ahmed, Khorshed, Rashid, & Gow, 2020)	Myanmar 1975-2014	Negative – 1 percent increase in military spending leads to 0.63 percent reduction in GDP
	Selected N Sample Studies	
Cappelen & Bjerkholt, (1984)	17 OECD countries 1960-1980	Negative effect
Dunne & Mohammad, (1995)	13 Sub-Saharan African countries 1967-1985	Negative effect (Time-Series Data), No effect (Pooled Data)
Landau, (1996)	17 OECD countries, 1950-1990	Inverted U shaped relationship
Blomberg, (1996)	70 countries, 1967-1982	Negative but weak effect
Stroup & Heckelman, (2001)	44 African and Latin American countries, 1975-1989	Inverted U shaped relationship
Aizenman & Glick, (2006)	81/83 countries, 1989-98	Positive impact in presence of security threats
Kollias, Mylonidis, & Suzanna-Maria, (2007)	15 European Countries- 1961-2000	Positive short-run impact
Yakovlev, (2007)	28 Countries- 1965-2000	Negative impact. Less detrimental effect when a country is a net exporter of arms
Karadam, Yildirim, & Ocal,(2016)	Middle Eastern Countries and Turkey- 1988-2012	Inverted U shaped
Aziz & Asadullah, 2017	70 Developing Countries – 1990-2013	Negative effect- Positive effect conditional upon internal threats
d'Agostino, Dunne, & Pieroni, (2019)	109 non- high income countries- 1988-2012	Negative affect

Table AP3.2 Full Results for Economic Growth Models (Full Sample)

	Model AP3.2.2	Model AP3.2.1
	Fixed Effect	**2SLS**
Military Expenditure/ GDP	-0.281*** (0.00) [0.070]	-1.10*** (0.00) [0.413]
Growth Rate$_{t-1}$	0.201 (0.00)	0.185 (0.00)
Change in Conflict Intensity	-0.758 (0.01)	-0.849 (0.01)
Logged Population	-0.482 (0.63)	-1.12 (0.23)
Ethnic Fractionalization	-5.43 (0.03)	-10.07 (0.00)
Life Expectancy	-0.017 (0.59)	-0.045 (0.16)
Inflation	-0.002 (0.05)	-0.01 (0.03)
Gross Fixed Capital Formation/GDP	0.088 (0.00)	0.099 (0.00)
Trade Openness	0.014 (0.00)	0.012 (0.00)
Non-Military Expenditures	-0.133 (0.00)	-0.139 (0.00)
Iran Iraq War (1980-88)	-1.63 (0.01)	-1.26 (0.03)
Gulf War (1990-91)	-0.885 (0.00)	-0.637 (0.00)
Post Cold War Era (1991-)	-0.540 (0.19)	-0.741 (0.05)
Financial Crisis (2008-09)	-2.67 (0.00)	-2.62 (0.00)

Oil Crisis/Recession (1974-75)	-1.59 (0.00)	-1.22 (0.00)
Country Fixed Effects	Yes	Yes
Prob > F	0.00	0.00
Observations	3985	3966

*Constant included in the model. Parentheses contain p-value whereas brackets contain Driscoll Kraay standard errors. *** p< 0.01, ** p< 0.05 and * p<0.10.*

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Chapter 4
Education and Participation in Political Violence: A Look Into Non-Linear Associational Patterns

Chapter 4 resulted in the following publication.

Saeed, Luqman (2018) " Education and Participation in Political Violence: A Look into Nonlinear Associational Patterns" *Peace Economics, Peace Science and Public Policy*, 24 (3): 1-11

4.1 Introduction

This paper presents fresh empirical evidence on the educational background of militants based on a sample from Pakistan. The study attempts to measure the likelihood of participation in political violence with respect to educational attainment through unweighted and weighted Probit model estimations of a consolidated dataset of 200 militants and a representative sample of over 13,000 Pakistanis. The present analysis covers militants involved in religiously motivated political violence. Not only that it happens to be the most prevalent and deadliest form of political violence in Pakistan but, as evident from linkages between international militant outfits such as Al Qaeda and Islamic State with militants based in Pakistan, threatens the international community as well (Saeed, Syed & Martin, 2014).[1]

Political violence is understood as violence or threat of violence perpetrated by individuals or subnational groups in pursuit of politically motivated agendas and whose audience is beyond that of the immediate victim.[2] The militants considered in this study are associated with outfits having explicit religiously-inspired political agendas. These outfits include Tehrik Taliban Pakistan (and its various splinter groups), Al Qaeda, Jaish e Muhammad, Sipah Sahaba of Pakistan, Lashker-e-Jhangvi and Islamic Movement of Uzbekistan. Ideologically, these outfits share common sets of ideas about the State and society, such as the imposition of Islamic law, despite certain strategic differences which might exist. For instance, both Lashker-e-Jhangvi and Tehrik Taliban Pakistan have common sectarian origins and regard minority sects such as Shiites as heretics. Both have perpetrated violence against the State and sectarian minorities. The only difference is that while Tehrik Taliban Pakistan concentrates targeting State employees and military, Lashker-e-Jhangvi specializes in the killing of members of the Shiite sect. In fact, many of the militants in the present sample maintained memberships in more than one of these outfits. This allows to pool these militants together and analyze general associational

[1] Religiously inspired militants such as Faisal Shahzad who attempted to carry out the bombing at Times Square New York was found to have linkages with militants based in Pakistan.

[2] This definition is inspired by the work of Enders and Sandler (2006). While they specifically define terrorism as such, this study prefers to use a more generic term of political violence.

patterns between education attainment and participation in the kind of violence these militants perpetrate. The descriptive analysis of the present dataset in Saeed and Syed (2018) provides quantitative account of the extent of collaboration between these outfits.

Peace science has made noteworthy advances in recent years towards providing a scientific explanations for the causes and consequences of political violence (Bassetti, Caruso & Schneider, 2018). On education-political violence nexus, whether it is the descriptive analysis of militants' educational backgrounds [for example on militants of Pakistani origins see Fair (2008) and Rassler, Fair, Ghosh, Jamal, and Shoeb (2013)], multivariate analysis of militants and comparable population [see Krueger and Maleckova (2003) and Berrebi (2007)] or aggregate analysis of education and political violence [see Caruso and Schneider (2013) and Bassetti, Caruso, and Schneider (2018)], positive correlation between proxies for education and violence has been observed in numerous cases. The contribution of the present study is that it measures the likelihood of participation in political violence w.r.t various levels of years of schooling and empirically demonstrates that the distribution of predicted likelihoods is characterized by an inverted U-shaped nonlinear pattern. The likelihood is maximum, having a magnitude of 2.81 percent, at around 12 years of schooling and starts declining thereafter. While individuals with such a level of education have the highest likelihood of being militant, there is no evidence found for a negative likelihood of participation in political violence at any level of schooling. Thus, the findings presented here seem to implicate that education attainment at all levels positively explains participation in political violence.

4.2 Brief Literature on Educational Background of Terrorists

Empirical analysis of political violence can be broadly categorized as the ones which take the occurrence and brutality of violence (proxied by incidents and victims, respectively) or perpetrators as a unit of analysis. In specific case of education-political violence nexus, there is evidence that seems to negate a universal pacifying effect of education on preferences or occurrence of political violence. For instance, Caruso and Gavrilova (2012) argu and empirically demonstrate that education in presence of adverse socioeconomic conditions can fuel political violence. In line with Choucri's (1974) thesis, they argue that education leads to economic expectations and if they are not fulfilled, for instance due to unfavorable macroeconomic conditions, can result in grievances and hence political violence. Particularly, the brutality of Islamist political violence is observed to be positively predicted by education (Caruso & Schneider, 2013).

The information on militants' attributes is not as easily available as acts of political violence. Limited information on militants from as diverse national settings as the United States, Pakistan, Bangladesh, Saudia Arabia, Palestine and others shared by the scholars seems to suggest an empirical consensus that militants are better educated than the population group they emerge from. Noteworthy contributions include the work of Krueger and Maleckova (2003), Berrebi (2007), Krueger (2008), Fair (2008), and Rassler et al. (2013). Fair (2008) and Rassler et al. (2013) found Pakistani origin militants in Kashmir to have comparatively better educational backgrounds than the average Pakistanis. Saeed and Syed (2018) developed a dataset with wider coverage of all types of militants from Pakistan and found similar results. Krueger and Maleckova (2003) estimated logistic regression on data of 129 Hizbollah fighters and a comparable Lebanese representative sample of almost 120,000 individuals. They found education to positively predict participation in Hizbollah's militancy. Krueger (2008) estimated the Probit model on consolidated data of 63 homegrown Islamist terrorists and a representative sample of 1050 Muslim Americans. The results indicated that an additional year of schooling increases the likelihood of being charged as terrorists by 4 percent. However, it is not clear from the study whether the marginal im- pact is an average or estimated at the mean. Also, in Probit estimation, the likelihood response of the dependent variable can be different for different values of explanatory variables. An interesting extension of the empirical methodology of Krueger (2008) could be the estimation of the likelihood of participation in political violence at different levels of years of schooling. This should also provide insights into the distribution of predicted likelihoods and help explore the relative strengths of the association of different levels of schooling with engagement in political violence. Figure 4.1 and Figure 4.2 illustrate patterns in the distribution of militants across different years of schooling in Krueger (2008) and the present dataset. However, it must be noted that Krueger's (2008) sample includes alleged militants who are either indicted or convicted; not just the individuals who have committed at least one attack. The present sample consists of perpetrators and this difference between the present sample and Krueger (2008) must be noted while comparing the findings.

Figure 4.1 Comparative Estimates on Educational Background of US Islamist Terrorists and Representative Sample of US Muslim Population (from Krueger, 2008)

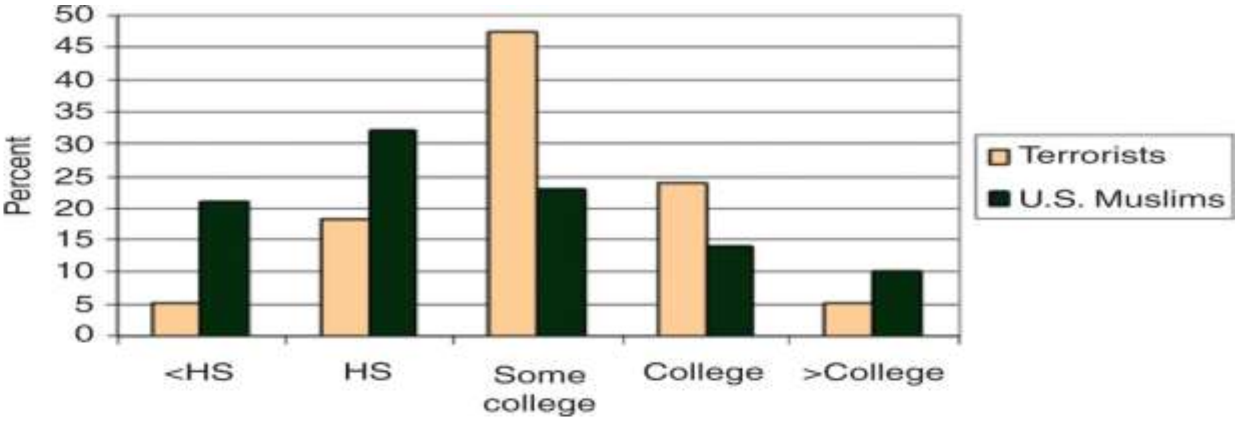
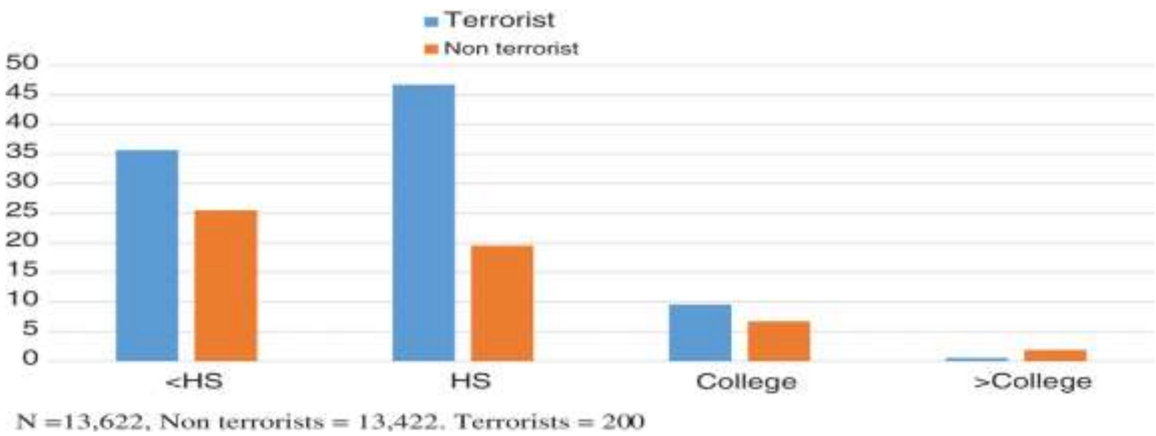


Figure 4.2 Comparative Estimates on Educational Background of Terrorists from Pakistan and Representative Sample of Pakistan's Population



The trend in Krueger (2008) suggests that US homegrown militants are better educated than comparable population towards higher years of schooling. In the case of militants of Pakistani origin, the trend seems to be reversed. The difference between the proportions of militants and non-militants seems to be larger at the lower end of years of schooling. Berrebi (2007) analyzed a much larger sample of almost 355 terrorists from Palestinian and over 40,000 individuals from a comparable population group. The final consolidated sample was roughly around 16,350 individuals. The results from logistic regression suggested that higher education and poverty are positively associated with participation in political violence. Findings from selected literature are summarized in Table 4.1 and an underlying consensus can be observed that militants have better educational background. However, it would be interesting to have a deeper look at predictions of being militants at different levels of education.

Table 4.1 Selected Literature on Educational Background of Terrorists

Study	**Sample Size**	**Methodology**	**Results**
Russel and Miller (1977)	350 (Marxist militants)	Descriptive/Patterns	Almost 2/3 of terrorists had either partial or full university education, or postgraduate degree
Post, Sprinzak, and Denny (2003)	35 terrorists (21 Islamist and 14 secular)	Interviews	"Most had high school, some had education beyond high school"
Krueger and Maleckova (2003)	129 deceased Hizbollah fighters and almost 120,700 comparable Lebanese population	Logistic Regression	Education is positively correlated with participation in political violence
Berrebi (2007)	355 terrorists	Multivariate Logistic Model	Education is positively correlated with participation in terrorism
MI5 classified report reported in the Guardian (2008)[a]	Several Hundred	Unknown	As published in the Guardian *Those involved in British terrorism are not unintelligent or gullible, and nor are they more likely to be well-educated; their educational achievement ranges from total lack of degree-level education. However they are almost all employed n low-grade jobs*
Fair (2008)	141 households of terrorist who fought in Kashmir	Descriptive comparative analysis with non-terrorist Pakistanis	Terrorists have comparatively higher level of education than rest of the population

Krueger (2008)	63 terrorists, 1050 non terrorists US Muslims	Multivariate, Probit estimation	An increase of 1 year of schooling leads to a 4 percent likelihood of being charged as a terrorist
Rassler et al. (2013)	917 deceased Lashker-Tayyba fighters from Pakistan	Descriptive	The most common level of education amongst militants is matric (10 years of schooling)
Riaz (2016)	112 militants from Bangladesh	Descriptive	Data on education was available for 65 militants. Students amongst them had all completed 12 years of schooling.

[a]See Guardian report at https://www.theguardian.com/uk/2008/aug/20/uksecurity.terrorism1.

4.3 Data and Methodology

The statistical model is estimated using an individual-level pooled dataset on almost 13,622 observations. The dataset is consolidated with information on the dependent and explanatory variables for both militants and non-militants Pakistanis. The dependent variable is a binary which equals 1 for militant and else 0. The explanatory variables include years of schooling, age, dummies for education attainment at below secondary (1–8 years), secondary & higher secondary (9–12 years), above secondary (13 years and more) and for provincial origins (i.e. Punjab, Sindh, Khybar Pakhtunkhwa (hereafter KPK), Balochistan). The information on attributes of militants is obtained from the Counter Terrorism Wing (CTW) of the Criminal Investigation Department (CID) of provincial police offices in Pakistan. To counter any selection bias that may plague government sources of information on militants, the data is augmented with information from private newspaper sources and biographical notes on militants published by Gul (2010). The total subsample of terrorists consists of 995 individuals and includes information on educational attainment, age and areas of origin. Further details and descriptive analysis of this dataset can be found in Saeed and Syed (2018). Only a proportion of militants from this dataset could be included in the present consolidated sample. First, militants for whom no information could be found on educational background had to be dropped.

Second, militants with only religious education reported were also dropped because no comparable religious education data was available for non-militant Pakistanis.

Further data cleansing was carried out to counter any double counting between militants and non-militants sub samples. Since the sample data for non-militants Pakistanis were collected during the year 2013, I only included those militants in the sample who were either convicted, absconded, or killed during that time. It should be noted that these are the militants who were involved in at least one incident of political violence. The data on a representative sample of Pakistanis is obtained from Pakistan Statistical Bureau (PBS). The data is a part of the PBS Household Integrated Economic Survey (HIES) which has been conducted periodically since 1963 to measure households' socioeconomic wellbeing. The information on education, age, and provincial origin is filtered from raw data of HIES for the present analysis. Both subsamples are pooled together to construct a consolidated data set of 13,622 individuals; 200 militants[3] and 13,422 non militants Pakistanis. Militants' sample is approximately 1.5 percent of the non-militants sample. The distribution of predicted probabilities of participation in political violence w.r.t education and other explanatory variables is modeled through both unweighted and weighted Probit regressions. Since militants are included endogenously in the sample, and may also be overrepresented, this may compromise randomness in selection. The results from such choice-based sampling may not be consistent. Hence, in line with Krueger and Maleckova (2003) and Berrebi (2007), the observations are weighted with a ratio of relative size in population to relative size in the sample.

The inclusion of provincial dummies in the model allows controlling for the region-specific impacts. Failure to do so might result in the variance of error term to be inconstant and correlated within provincial clusters because of the idiosyncratic impacts that occur within. Table 4.2 presents some descriptive statistics on age and years of schooling. Militants seem to be on average relatively younger

[3] The drop in the sample size from 995 to 200 militants is entirely due to the unavailability of data on educational backgrounds for all militants in the sample. While this can lead to inconsistent estimates due to choice-based sampling, but, as suggested in Krueger and Maleckova (2003) and Berrebi (2007) the problem can be mitigated by estimating the models using observations weighted with the ratio of size of militants in population to their size in the sample.

than the comparable population. They also have 4 years more of average schooling than the rest of the population.

Table 4.2 Descriptive Statistics

	Terrorist	**Non Terrorist**
Age	35 (17 min- 68 max)	46 14 min-99 max)
Avg. years of schooling	9 (0 min-17 max)	5 (0 min- 23 max)
Total	200	13422
Punjab	41 %	51 %
Sindh	20 %	25 %
KPK	35 %	15 %
Balochistan	4 %	9 %

4 .4 Results

The results from the estimated Probit models are reported in Table 4.3. Multiple models are estimated and evaluated with relevant goodness of fit tests. First, I estimate a model which controls for years of schooling, age, and provincial origin dummies. The sign of the estimated coefficient for years of schooling indicates that an increase in this variable is associated with a positive likelihood of participation in political violence. However, the null hypothesis for the Hosmer-Lemeshow test that the fitted model is correct is rejected (p-value 0.00, see Model 4.31). Therefore, we cannot accept estimates from Model 4.3.1 as an approximate good fit for the data. In Mode 4.3.2, I include a quadratic term for years of schooling variable. Interestingly the estimated Model 4.3.2, which controls for nonlinear relationship between education and participation in political violence, seems to best fit the data as indicated by the p-value for Hosmer-Lemeshow test statistic. There is no evidence to reject the null hypothesis that the fitted model is correct (p-value 0.24, see Model 4.3.2). Although the mean-variance inflation factor is 5.67, the statistical significance of individual estimates and the overall significance of the model does not indicate any serious multicollinearity issue. The estimated value of the Bayesian Information Criterion (BIC) also suggests Model 4.3.2 to perform better than Model 4.3.1. The negative sign with the estimated coefficient of the quadratic term suggests that the distribution of predicted probabilities of being militant in relation to years of schooling is characterized by an inverted U -shape form.

Table 4.3 Results for Unweighted Probit Estimates

Variables	**Model 4.3.1**	**Model 4.3.2**	**Model 4.3.3**
Constant	-1.98** (0.224)	-2.25*** (0.231)	-2.26*** (0.233)
Years of schooling	0.056*** (0.006)	0.163*** (0.021)	0.054*** (0.022)
Years of schooling^2		-0.007*** (0.001)	
Below secondary (1=Yes)			0.383** (0.176)
Secondary and higher secondary (1= Yes)			0.399 (0.260)
Above higher secondary (1=Yes)			-0.071 (0.386)
Age	-0.037*** (0.003)	-0.035*** (0.034)	-0.035*** (0.003)
Punjab	0.785*** (0.191)	0.695*** (0.190)	0.721*** (0.190)

Sindh	0.607***	0.536***	0.563***
	(0.198)	(0.197)	(0.197)
KPK	1.45***	1.38***	1.41***
	(0.192)	(0.190)	(0.191)
Pseudo R^2	0.20	0.22	0.22
LR $\chi 2$	413.73	448.62	446.87
Prob > $\chi 2$	(0.00)	(0.00)	(0.00)
Hosmer-Lemeshow test	2566.25	2211	2211
Mean-variance inflation factor	2.61	5.67	10.51
Bayesian information criterion	1661.25	1635.88	1656.71
No. of observations	13622	13622	13622

The dependent variable is in binary form (1 = Terrorist, 0 otherwise). Parentheses contain robust standard errors whereas *, **, *** denote significance levels of 10 percent, 5 percent, and 1 percent, respectively.

I also estimated unweighted models with different proxies for education such as dummies that capture education at different levels; however, the goodness of fit tests suggest Model 4.3.2 to be the best model. In Model 4.3.3, I report the second best estimated model amongst unweighted models in which quadratic term for years of schooling is dropped due to high correlation with dummies for different levels of education. The fitted model is correct as suggested by the p-value for the Hosmer-Lemeshow test but does not perform as well as Model 4.3.2. Also, mean VIF is quite high which indicates strong collinearity between explanatory variables, which in turn might be affecting the statistical significance of the estimated coefficient for a dummy for higher education by inflating the standard error.[4]

[4] I also estimated model with only dummies for education level but the model does not fit the data as indicated by goodness of fit test. This relationship is best captured when education is controlled as continuous variable in both linear and quadratic form. In another model I also added square term for age but again the model did not pass goodness of fit test

The weighted regression results are reported in Table 4.4 reveal similar patterns between education and participation in political violence. In fact, as indicated by the value for Pseudo R^2 of 0.37, the weighted models capture more variations in the dependent variable than unweighted estimated regressions (see Table 4.3). Model 4.4.1 suggests similar inverted U-shaped relationship as in Model 4.3.2. In model 4.4.2 which is likewise specified as Model 4.3.3, except that it is weighted, the estimates for dummies for education at various levels follow a similar pattern.

Table 4.4 Results for Weighted Probit Estimates

Variables	**Model 4.4.1**	**Model 4.4.2**
Constant	-3.21***	-3.22**
	(0.204)	(0.209)
Years of schooling	0.124***	0.039***
	(0.015)	(0.012)
Years of schooling^2	-0.005***	
	(0.0009)	
Below secondary (1=Yes)		0.309***
		(0.114)
Secondary and higher secondary (1= Yes)		0.324***
		(0.154)
Above higher secondary (1=Yes)		-0.029
		(0.246)
Age	-0.025***	-0.025***
	(0.002)	(0.002)
Punjab	0.551***	0.569***
	(0.161)	(0.161)
Sindh	0.440***	0.460***
	(0.164)	(0.165)
KPK	1.05***	1.07***
	(0.161)	(0.162)
Pseudo R^2	0.15	0.15

Wald $\chi 2$	326.47	328.95
Prob > $\chi 2$	(0.00)	(0.00)
Mean-variance inflation factor	5.63	10.41
Bayesian information criterion	66.64	85.68
No. of observations	13622	13622

The dependent variable is in binary form (1 = Terrorist, 0 otherwise). Parentheses contain robust standard errors whereas *, **, *** denote significance levels of 10 percent, 5 percent, and 1 percent, respectively. The weights for terrorists and non-terrorist samples are 0.00047 and 0.0068 percent, respectively

This positive and negative sign for linear and quadratic years of schooling, respectively implies that initially an increase in educational attainment is associated with a positive likelihood of being a militant. However, this positive relationship holds to a certain level of education after which the change in likelihood is negative. The level of educational attainment with the maximum likelihood of being militant is calculated by taking the derivative of estimated function w.r.t to years of schooling and setting the resultant equivalent to 0

$$0.163 - 0.014X = 0$$

$$X = 0.163/0.014$$

$$X = 12.38 \approx 12 \text{ years of schooling}$$

This suggests that the probability of being militant increases starting from 1 year of schooling and peaks around roughly 12 years of education. In Pakistan, the nomenclature for this level of schooling is intermediate and internationally it is regarded as high school level of education. The likelihood of being militant starts declining thereafter but remains above 2 till 17 years of education which is roughly equivalent to one year of master's. The year of schooling which maximizes weighted function is 12.4≈12 years of schooling. The average marginal impacts are reported in Table 4.5. The results indicate that 1 year of additional schooling is associated with approximately 0.1 percent of the average likelihood of being militant. The predicted probabilities for provincial dummies suggest some important insights too. For instance, individuals originating from Punjab, Sindh, and KPK are more likely to be militant than the base province Baluchistan by the magnitude of 2, 1.5, and 4 percent, respectively.[5]

Table 4.5 Average Marginal Impacts

Variables	For Model 4.3.2 (Unweighted	For Model 4.4.1 (Weighted)
Years of schooling	0.001***	0.0001***
	(0.0002)	(0.00001)
Age	-0.001***	-0.00007***
	(0.0001)	(0.000008)
Punjab	0.020***	0.002***
	(0.005)	(0.0004)
Sindh	0.015***	0.001***
	(0.005)	(0.0004)
KPK	0.040***	0.003***
	(0.005)	(0.0005)

The dependent variable is in binary form (1 = Terrorist, 0 otherwise). Parentheses contain robust standard errors whereas *, **, *** denote significance levels of 10 percent, 5 percent, and 1 percent, respectively. The weights for terrorists and non-terrorist samples are 0.20 and 0.006, respectively.

The distribution of change in predicted probabilities with incremental change in years of schooling is presented in Table 4.6 and Table 4.7. In the Probit model estimation P($y = 1/x$) does not necessarily remain constant for different values of X. The following formula is used to estimate the change in predicted probabilities in response to a change in years of schooling.

Table 4.6 Distribution of Change in Predicted Probabilities of Being a Terrorist (Unweighted Estimates)

Years of schooling	Predictive margins	Change in predictive margins
1	0.44	
2	0.63	0.19
3	0.85	0.23

[5] The dummy for Balochistan is dropped to due perfect collinearity between the provincial dummies.

4	1.12	0.26
5	1.40	0.28
6	1.70	0.30
7	1.99	0.29
8	2.26	0.27
9	2.49	0.23
10	2.66	0.18
11	2.77	0.11
12	2.81	0.04
13	2.78	-0.03
14	2.67	-0.11
15	2.50	-0.17
16	2.27	-0.23
17	2.01	-0.27
18	1.72	-0.29
19	1.42	-0.30
20	1.13	-0.29
21	0.87	-0.26
22	0.64	-0.23
23	0.45	-0.19

Table 4.7 Distribution of Change in Predicted Probabilities of Being a Terrorist (Weighted Estimates)

Years of schooling	**Predictive margins**	**Change in predictive margins**
1	0.03	
2	0.04	0.01
3	0.06	0.02
4	0.08	0.02
5	0.10	0.02
6	0.12	0.02
7	0.14	0.02

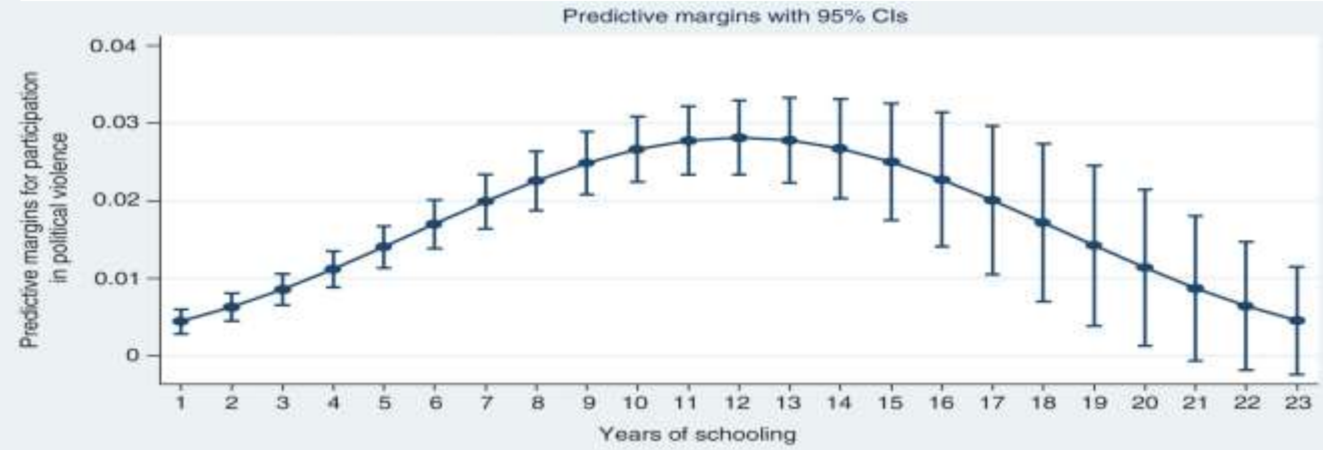
8	0.16	0.02
9	0.18	0.02
10	0.20	0.01
11	0.21	0.01
12	0.21	0.00
13	0.20	0.00
14	0.19	-0.01
15	0.18	-0.01
16	0.16	-0.02
17	0.14	-0.02
18	0.12	-0.02
19	0.09	-0.02
20	0.07	-0.02
21	0.06	-0.02
22	0.04	-0.02
23	0.03	-0.01

Δ in predicted probability = $[\mathrm{pr}(y|x, x_t + \Delta) - \mathrm{pr}(y = 1|x, x_t)]$

where *y* is =1 for militant and else 0 and *x* is years of schooling.

The estimates in Table 4.6 suggest a progressive increase in the likelihood of being militant from 0 to 12 years of schooling. In fact, the probabilities remain over 2 percent from 8 to 17 years of schooling; maximizing at 12 years (also see Figure 3). Nevertheless, the change in likelihoods beyond 12 years of schooling is negative within the range of 0.1–0.3 percent (see column 2, Table 4.6). These findings run contrary to the perception that political violence originates in illiteracy and suggests that those with better education are more likely to be militants.

Figure 4.3 Distribution of Predictive Marginal Probabilities of Participation in Political Violence w.r.t Years of Schooling



4.5 Discussion

The results presented in this paper provide reasonable evidence for nonlinear relationship between education and participation in political violence. This is an important finding because it reveals the range of years of schooling which is more likely to produce participants in political violence.

To an extent, this study supports the findings implicated in descriptive work of Post, Sprinzak, and Denny (2003), Rassler et al. (2013), and Riaz (2016) on militants from Palestine, Pakistan, and Bangladesh, respectively, that militants are more likely to have a secondary and higher secondary level of education. While it is beyond the scope of the present study to say anything conclusive about the theoretical aspect of the positive impact of education on participation in political violence but two important reflections might contribute to some preliminary understanding. First, the curriculum taught in Pakistani schools, particularly, the public schools is infested with the material in social sciences and humanities that glorifies violence and promotes religious exclusivism. It is possible that such educational contents develop world views which makes some individuals vulnerable to militant outfits' propaganda. This is in line with the conclusions of Berrebi (2007) who rested responsibility on the educational curriculum for explaining positive interaction between education and participation in terrorism amongst Palestinians. Nayyar and Salim (2005) provide a comprehensive assessment of the radical curriculum taught in Pakistani schools. They identify Pakistan Studies and Islamic Studies as the subjects which carry the major proportion of radical contents. The relative weight of these subjects is higher during below and higher secondary education and coincidently it is at these levels of education that likelihood of participation in political violence increases and maximizes. While the stress and relative size of these subjects during the specialized university education is less, with the exception if specialization is pursued in these subjects, the change in the likelihood of engaging in political violence also becomes negative. Perhaps, the likelihoods starts declining because there is counter economic pull as specialized education increases prospects for livelihood from legitimate activities. Nevertheless, the positive impact at higher education does not disappear and if radical contents are to blame, then it could be argued that the worldviews established during earlier years of schooling persist as individuals are not exposed to any counter-radical curriculum which could reduce their vulnerability before radical propaganda.[6] It might be the combination of susceptibility to radical religious ideology and the expertise gained through education that makes such individuals attractive assets for recruitment by radical outfits. If radical contents are indeed responsible for the "educated militant" phenomenon, then in view of the fact that at no level of schooling there is the negative likelihood of participation in political violence is observed, then nothing less than a complete redesigning of the curriculum in social science and humanities, as advocated by Nayyar and Salim (2005), will be required.

In addition to radical curriculum theory, it could also be argued that the individuals with secondary and below education are more likely to become militants because the economic opportunities are comparably less for them. This might decrease their opportunity cost for participation in political violence. This is the line of thought presented by Caruso and Gavrilova (2012). It is not possible to empirically demonstrate it due to the lack of data on the economic backgrounds of the participants covered in the study. However, some support for this view emerges from a regression in which I

[6] Some universities such as Lahore based Forman Christian College (A Chartered University) offer liberal arts program intended to produce a diversified and tolerant worldview by exposing student to various academic courses in social sciences and humanities incorporating internationally accepted curriculum other than their specialized disciplines. Unfortunately, such universities are exception.

controlled for socioeconomic indicators of districts of origins. The results revealed the same pattern between education and political violence but further revealed that militants are more likely to emerge from socioeconomically deprived regions. However, nothing conclusive can be said in absence of lack of individual level data on the economic status of those in the sample. The investigation on the mediating impact of ideology and economic factors is much larger project and should be a way forward in this research; and once anything conclusive is found about the casual mechanism that proper policy prescription can be pronounced. The main contribution of the present study is that it reveals nonlinear relationship between education and participation in political violence and also the range of years of schooling which predict involvement with comparably higher order of probabilities.

4.6 Limitations

The present empirical analysis is not without limitations. Modelling engagement in political violence is not an easy subject because of lack of relevant data and acknowledging them will help towards better utilization of the findings and suggest way forward without compromising the validity of some of the core findings of present research. First, because of the unavailability of individual level data on religious education for "normal Pakistanis" I have only been able to control for non-religious education (non-seminary education, public and private schools and colleges). However, as demonstrated in Saeed and Syed (2018) the contribution of militants from religious institutions is low in absolute numbers (although they contribute disproportionate to their size in national sample) and overall militants, as compared with rest of the nation, have disproportionately higher education attainment at various levels of education from non-religious institutions. Missing out those with religious education may result in losing important insights but because those educated from non-religious constitutes in-sample majority, do not necessarily invalidate the analysis.

Second, I caution readers that these results should not be taken as concrete evidence for causal impact of education on becoming a militant. The caution is maintained in order to not to seem too ambitious and far-stretched with present empirical analysis although the reasons on which caution is based are not entirely intractable even at present.[7] Nevertheless I recommend that the findings should only be used to support the view that individuals with education attainment roughly at the level of high school (12 years, i.e. intermediate level of education as known in Pakistan) have comparatively higher likelihood to be militants.

The causality can only be established until we are able to present a concrete theoretical basis for relationship between education and participation in terrorism. For instance, if these results do indicate an underlying causal dynamic, it is not possible, with limited information at present, to theorize that whether it is the ideological component of education which drives some individuals towards religious militancy or, perhaps, it is because of lack of economic opportunities for individuals which lowers the opportunity cost of participation in violence, or is it the combination of both factors? None of it could be true and it is possible that terrorist outfits consider individuals with education from non- religious institutions as more suitable for their operations as such individuals are better able to integrate in society. Since we do not have information on variables such as income levels, exposure to militants' literature etc. therefore, we cannot say anything conclusively about causal mechanism. However, it might be pertinent to mention here that many reputed scholars have convincingly argued that curriculum taught in Pakistani schools promote bigotry, religious exclusivism and glorifies violence (Nay- yar & Salim, 2005; Graff & Winthrop, 2010). This seems to suggest an ideological impact of education which drives conflict in society. Nevertheless, this remains to be an area which requires further rigorous empirical investigation.

Third, some critic might argue that in a multivariate setting, where dependent variable is a dummy for militant, independent control for education attainment could itself be correlated with error term and hence the model suffers from endogeneity problem. There are some intuitive and empirical reasons to assume that this might not be the case. Figure 2 demonstrates that the distribution of terrorists across different levels of educational attainment is roughly negatively skewed with higher proportion

[7] For instance, significant literature already exists that expose religiously inspired radical elements in curricula taught in Pakistani educational institutions particularly at schools. It would not be farfetched to assume that this might drive some individuals towards religiously motivated violence. For more on curricula see Nayyar and Salim (2005).

concentrated around “non-technical & non-specialized” non-university education. As the non-university education in Pakistan (from 1 to 12 years) does not confer any serious technical or specialized knowledge that militants could exploit (such as knowledge from natural and management sciences for operational and organizational purposes), it is hard to imagine that why an individual with inclination towards political violence, or already is a militant, would be incline towards more education.

In fact, in an ironic twist, while on one hand educational curriculum might be contributing towards making some unknown proportion of individuals soft targets for militant outfits propaganda, as implicated by Nayyar and Salim (2005) study on radical curriculum contents in Pakistan, the non-religious educational institutions are themselves one of the prime targets of militant outfits for dispensing “western oriented” education. In other words, not that we cannot expect potential militants to seek any non-specialized education for it confers no operational or organization utility, we also cannot expect any inclination for more education in pursuit of further intellectual radicalization; for once an individual is radicalized, it is reasonable to assume that it is not the arena of mainstream educational institutions rather the association with outfits which becomes attractive for further intellectual training in radical beliefs. Militants such as Saad Aziz and Nooren Laghari either started having bad grades after becoming radicalized or left studies in the middle to join Jihadist groups. Hence, the reverse impact of being terrorist on education does not seem convincing in the light of these observations.

4.7 Conclusion

This paper presents findings on nonlinear relationship between education attainment and participation in political violence. The empirical analysis is based on dataset on militants and non-militants Pakistanis. Overall the findings support the view that political violence originates in literacy and within literate population, militants are more likely to emerge from high school background. At no level of education, the likelihood of participation in political violence is negative. Hence, the findings support the view that political violence positively correlates with education. In Pakistani context, it seems that it is the radical content of education which is likely to explain such causal linkage, however, future research would need to investigate it more thoroughly.

Conclusion

This thesis is a collection of four essays in which I employ econometric methodologies to examine the impacts of humanitarian military interventions, drone strikes and educational attainment on various forms of political violence. I also estimate the impacts of humanitarian military interventions and military expenditures on economic growth.

In Chapter 1 I investigate the impact of humanitarian military interventions (HMIs) on conflict termination and escalation, human rights observance and economic growth. The empirical analysis are based on a new database on HMIs. To identify the causal impact, I run IV regressions using instruments generated by exploiting the heteroscedasticity in the errors of the endogenous covariate, i.e. HMIs. The results show that the biased HMIs escalate conflict and lead to a large negative affect on economic growth. In addition to escalating conflict, against government HMIs also adversely affect human rights observance. Neutral HMIs, in which interveners target all perpetrators of violence, are observed to have positive affect on conflict termination.

Chapter 2 is co-authored with Professor Michael Spagat and studies the impact of US drone strikes on suicide bombings in Pakistan. The drone strikes variable is modelled as an endogenous covariate in the econometric model for suicide bombings because of the possible reverse causality and the effects of omitted unobserved factors. We use weather conditions as instruments for drone strikes which affect drones' operations but are unrelated to suicide bombings. The results from IV regressions show a large causal impact of drone strikes on suicide bombings. According to the estimates, a drone strike is followed by 1 suicide bombing in the following month.

In Chapter 3, I use value of arms imports during peace time and number of neighboring states with interstate violence as instruments for military expenditures in an endogenous growth model. The results indicate that a 1 percentage points increase in military expenditure/ GDP leads to around a 1.20 percentage points reduction in economic growth. This negative affect is particularly stronger in sample of countries with below than average human rights observance. The results from several diagnostic tests show that instruments are strong and satisfy overidentification restrictions.

Finally In Chapter 4 I use a self-created novel database on militants of Pakistani origin to examine the impact of education attainment on participation in political violence. This data is consolidated with a representative sample of around 13422 other Pakistanis. The results from weighted and unweighted probit estimations suggest that the education attainment has a nonlinear association inverted U shaped relationship with participation in political violence. The likelihood of participation in political violence maximizes at around 12 years of schooling.

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